CHAPTER

10

Hybrid brain–computer interfaces for wheelchair control: a review of existing solutions, their advantages and open challenges

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CHAPTER OUTLINE

Brain–computer interfaces (BCIs) had their initial development for military use, with the goal of increasing the performance of soldiers with equipment controlled by the mind (Wolpaw et al., 2000). Today, this technology has been mainly used in applications to replace, restore, and improve the outputs of the central nervous system (Wolpaw and Wolpaw, 2012). For example, BCIs have been used in rehabilitation (Daly and Wolpaw, 2008), to improve communication (Kübler et al., 2001), in computer gaming (Nijholt, 2009), wheelchair locomotion (Fernández-Rodríguez et al., 2016), and even in experiments with interaction between two humans (Wang and Jung, 2011).

The classical definition for a BCI was established more than a decade ago during the first International BCI Meeting, which set a BCI as a brain–controlled communication and control system independent of the pathways of peripheral nerves and muscles (Wolpaw et al., 2000). However, with the crescent number of techniques used to improve BCI setups and the range of emerging applications, its definition was updated to a closed-loop system that is (1) intentionally modulated by the

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user, (2) based on signals recorded directly from the brain, (3) which are processed in real time, and (4) that provides a real-time feedback to the user (Pfurtscheller et al., 2010a).

This last definition also fits the new field of "hybrid" BCI (hBCI) that exploits the conjunction of different brain and body monitoring methods to achieve more accurate and comprehensive systems. Pfurtscheller et al. (2010a) compare the hBCI to hybrid cars, which have two engines, one based on gasoline and other on electricity, to enhance their energy efficiency and to reduce their CO_2 output. Similarly, an hBCI can use two different brain tasks, such as an imagery-based and an attention-based task, to increase the final performance and reduce the illiteracy index (number of individuals who are unable to control a BCI system based on a particular task) (Banville and Falk, 2016).

This chapter aims to discuss the state-of-the-art of hBCI systems, with particular focus in the context of smart wheelchairs. First, we introduce some concepts of hBCI, such as its definition, recording methods, neural responses, and how they interact to become an hBCI, as well as some hBCI categorizations. We also present and discuss some existing applications, with special attention to wheelchair and locomotion control. We then describe the advantages and disadvantages of this technique and, finally, discuss available low-cost biosensors to create an hBCI system and point out future challenges in this area.

10.1 CONCEPTS OF HYBRID BRAIN–COMPUTER INTERFACES

A simple and highly accepted definition of hBCI is a system that combines two or more signals from different origins, including at least one input recorded directly from the brain (Allison et al., 2010). This definition is sufficiently comprehensive to encompass the merge of different recording modalities or the mix of different neural response patterns from a single modality (Banville and Falk, 2016). Concerning possible mixtures of techniques and approaches, it is also possible to categorize hBCI into different types of combinations (Allison et al., 2010). A pure hBCI, for example, combines different BCI approaches but exclusively using neural recording modalities. One example of a pure system is a merge of two different EEG tasks. A physiological hBCI, otherwise, combines at least one BCI task with one or more physiological signals, such as electroencephalography (EEG) signals with peripheral recordings (e.g., electrocardiogram, ECG) to evaluate the user's stress or fatigue. Last, a mixed hBCI is a system that combines one BCI signal with a nonphysiological input, such as a task involving a neural signal and a joystick response.

Considering the brain–imaging techniques, which are commonly used to compose an hBCI system, two main groups can be identified. First, those based on cerebral blood flow measures, also called hemodynamics, and second, those based on electrical or magnetic resultants from dipole sources created by electrical activity in neurons and synapsis (Min et al., 2010) (Fig. 10.1A).

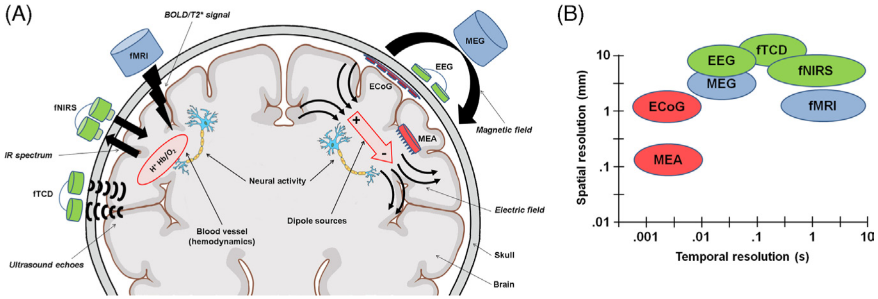

FIGURE 10.1

(A) Principles of neural activity recording of each neural-based technique. (B) Comparison of temporal and spatial resolution of these techniques. Light gray (Green in Web versions) methods are portable and noninvasive, Dark gray (blue in Web versions) methods are nonportable and noninvasive, while black (red in Web versions) methods are mobile and invasive.

Source: (A) From Min, B.K., Marzelli, M.J., Yoo, S.S., 2010. Neuroimaging-based approaches in the brain–computer interface. Trends Biotechnol. 28 (11), 552–560; (B) From Van Gerven, M., Farquhar, J., Schaefer, R., Vlek, R., Geuze, J., Nijholt, A., et al., 2009. The brain–computer interface cycle. J. Neural Eng. 6 (4), 041001.

Functional magnetic resonance imaging (fMRI) is the most used hemodynamic-based tool for noninvasive BCI due to its superior spatial resolution. This technique is based on the detection of the local blood oxygenation level dependent (BOLD) signal during neuronal activation (Min et al., 2010). However, the lower temporal resolution and the expensive and static setup inhibit its use in portable and real-world applications (Van Gerven et al., 2009). Functional near-infrared spectroscopy (fNIRS) and functional transcranial doppler (fTCD), on the other hand, are two portable techniques with higher temporal resolution (Fig. 10.1B) that have seen tremendous growth over the last decade. fNIRS uses the infrared spectrum to characterize alternations in the intensity of attenuated light resulting from changes in oxyhemoglobin (HbO2) and deoxyhemoglobin (Hb) concentrations, while fTCD uses ultrasound Doppler to measure the velocity of blood flow in the main cerebral arteries during local neural activity (Min et al., 2010).

The EEG, in turn, uses simple electrodes on the scalp to measure electric potentials generated by neural activity (usually the sum of excitatory and inhibitory postsynaptic potentials of groups of neurons). The high temporal resolution and portability of EEG make it the most commonly used technique in real-world experiments (Van Gerven et al., 2009). In contrast, magnetoencephalography (MEG) uses a superconducting quantum interference device (SQUID) around the scalp to record the magnetic disturbance created during neuronal activity (Min et al., 2010). Like fMRI, MEG's expensive, and static setup makes it unusable for portable applications.

Invasive approaches are also of interest to hBCI and neurofeedback systems. The electrocorticography (ECoG) uses electrodes placed on the surface of the cortex, while multielectrode array (MEA) uses electrodes implanted into the cortex. Interest in these methods derives from the high dimensionality and signal quality provided (Gürkök and Nijholt, 2012). However, the necessity of a surgical procedure and subsequent risk of infection make these techniques feasible only for applications in extreme cases. For this reason, we do not discuss invasive modalities here.

Other physiological measures commonly applied to hBCIs are the electromyograph (EMG) for muscular biopotential recordings (Leeb et al., 2011; Perdikis et al., 2014), the electrooculograph (EOG) for eye movement evaluation (Jiang et al., 2014; Wang et al., 2014), and the electrocardiograph (ECG) for heart biopotential monitoring (Sato et al., 2013; Shahid et al., 2013). Peripheral measures, such as skin conductance response (SCR), which measures the electrical conductivity of the skin, the photoplethysmograph (PPG), which monitors local changes in microvascular blood volumes, and other measures like temperature, blood pressure, and respiration rate are also used in hBCI approaches (Banville and Falk, 2016). Finally, nonphysiological equipment, such as eye tracking (Yong et al., 2011, 2012; Zander et al., 2010), keyboard (Mühl et al., 2010), and a game controller (Kreilinger et al., 2011; Leeb et al., 2013) have also been used for mixed hBCI approaches.

Recording neural activity related to different mental efforts and from various brain regions is a significant factor for the variability of BCI signatures (referred here as neural responses and exemplified in Table 10.1) (Curran and Stokes, 2003). It is possible to divide these neural response patterns into three major groups: evoked and induced responses, both related to electrical activities, and the hemodynamic response function (HRF), related to metabolic blood flow.

Evoked responses are usually time- and phase-locked by an internal or external event (Curran and Stokes, 2003; Van Gerven et al., 2009). One of the simplest signals used to drive a BCI is the slow cortical potential (SCP), an operant conditioned process of self-regulation of brain potentials. It does not require continuous feedback, but an extensive training period and the demand for rewards for achieving the desired potential becomes necessary (Birbaumer, 1999). Event-related potentials (ERP), otherwise, are negative or positive deflections caused right after a particular stimulus. The ERP most often used in BCI applications is the P300, whose positive component is identified roughly 300 ms after the stimulus. In visual experiments, the user focuses on a single stimulus and ignores the others, registering a P300 when the desired stimulus is triggered (Farwell and Donchin, 1988). Another type of ERP is the error potential (ErrP), measured when an individual recognizes a mistake that was made. Its signature involves a negative deflection 50–100 ms after the event, followed by a positive one around 200–400 ms after the onset (Schalk et al., 2000). Finally, another group of evoked responses is the steady-state evoked potential (SSEP), which occurs when an oscillatory sensory stimulation is performed at a constant frequency, causing the corresponding sensory cortex to present phase-locked spectral oscillations with the stimulus. Similar to the P300, the user focuses on one stimulus among several to present the corresponding pattern, enabling fast-response BCI applications without the need for long training times (Vialatte et al., 2010).

Table 10.1 Most Common Neural Response Patterns Applied to BCIs, Their Characteristics, and Regions of Interest

Neural Response Pattern	Example	Characteristics	Region of Interest
Slow cortical potentials (SCPs)	—	Slow oscillations in the EEG arising from cortical polarization lasting from several hundred milliseconds to several seconds	Frontal and central regions
Event-related potentials (ERP)	P300	Positive deflection in amplitude around 300 ms after the presentation of a rare stimulus	Parietal and occipital regions
	Error potential (ErrP)	Negative deflection 50–100 ms and a positive deflection around 200–400 ms after the recognition of an error that was made	Fronto-central and fronto-parietal regions, respectively
Steady-state evoked potentials (SSEP)	Steady-state visually evoked potentials (SSVEP)	Phase-locked spectral activity with the same frequency as the visual rhythmic stimulation	Occipital region
	Steady-state somatosensory evoked potentials (SSSEP)	Phase-locked spectral activity with the same frequency as the tactile rhythmic stimulation	Central region
	Steady-state auditory evoked potentials (SSAEP)	Phase-locked spectral activity with the same frequency as the auditory rhythmic stimulation	Parietal region
Sensorimotor activity	Event-related desynchronization (ERD)	Fade out of rhythmic activity in the 8–12 Hz and 13–30 Hz ranges when a voluntary movement is triggered or imagined	Central, frontal, and parietal regions
	Event-related synchronization (ERS)	Resurgence of rhythmic activity in the 8–12 Hz and 13–30 Hz ranges when a voluntary movement is over	Central, frontal, and parietal regions
	Movement-related potential (MRP)	Low-frequency pattern that arises around 1–1.5 s before a movement occurs	Central, frontal, and parietal regions
Hemodynamic response function (HRF)	Blood oxygenation level dependent (BOLD)	Increase in blood flow and oxygenation with varied strength and spatial distribution after the occurrence of neural activity	All brain

However, induced responses have power, rather than phase, time-locked to the stimulus, which means that the power in specific frequency bands needs to be explored to identify the desired response (Van Gerven et al., 2009). The most studied response of this group is the sensorimotor activity, especially μ (8–12 Hz) and β (13–30 Hz) frequency changes that arise with motor execution (ME) or imagery (MI). Whenever a voluntary movement is started or imagined, a phenomenon termed event-related desynchronization (ERD) occurs with an attenuation of the power in μ and β frequency bands (Pfurtscheller and Aranibar, 1977; Pfurtscheller and Da Silva, 1999). Similarly, an event-related synchronization (ERS) rebound appears when the movement is over, with an increase in power at these frequencies (Pfurtscheller 1992; Pfurtscheller and Da Silva, 1999). Another type of sensorimotor response is the movement-related potential (MRP), a bilaterally low-frequency potential around 1–1.5 s before a movement occurs (Shibasaki et al., 1980; Toro et al., 1994). Last, induced responses are also found in other mental tasks, such as the desynchronization after selective attention tasks (Van Gerven and Jensen, 2009), motor rotation (Millán et al., 2004), mental arithmetic (Chochon et al., 1999), and language-related tasks (Petersen et al., 1988).

Unlike electrophysiological responses, hemodynamic brain activity is not as diverse. The most typical response pattern explored is the hemodynamic response function, a variation in oxygen consumption and blood flow following increased neural activity in the brain (Fox and Raichle, 1986). This small BOLD change is the most common pattern used in experiments using fMRI and fNIRS approaches (Buxton et al., 2004). This response, however, presents strength and spatial variation according to the mental task (Cabeza and Nyberg, 2000), as well as between subjects or from one day to the other (Aguirre et al., 1998), causing many hemodynamic BCIs to target mental tasks that induce different spatiotemporal patterns (Naseer and Hong, 2015).

Considering all the combinations available with different techniques and neural response patterns, Pfurtscheller et al. (2010a) divided hBCI approaches into two groups according to their interaction between techniques and/or patterns: (1) sequential and (2) simultaneous hBCI.

A sequential hBCI presents components working in series, one after the other. The first use of this approach is the first element acting as a "brain switch" to activate or deactivate the second component. As illustrated in Fig. 10.2A, an ERD or ERS pattern can serve as a switch to turn on the SSVEP menu, which controls the direction of wheelchair movement. Another usage is the first component acting as a selector to choose between multiple possible options. Figure 10.2B shows a P300 menu, which selects the direction while the SCP pattern controls the duration or the velocity of the wheelchair movement.

A simultaneous hBCI, in turn, has components working in parallel using some form of fusion strategy. A possible application is the use of two or more elements in competition or complementarity, as shown in Fig. 10.2C, where the direction selected based on an SSVEP menu might be changed according to an obstacle detected by a distance sensor.

The fusion of a simultaneous hBCI may be established at different moments of the BCI process (Gürkök and Nijholt, 2012). Data-level fusion, for example, occurs when unprocessed signals carrying similar information are fused, as illustrated in Fig. 10.3A. This type of fusion is typically used for similar data or those recorded by the same equipment, such as using EMG and EOG for filtering an EEG signal. The advantage of this fusion level is the avoidance of loss of information. However, it is also more sensitive to noise and modality failures.

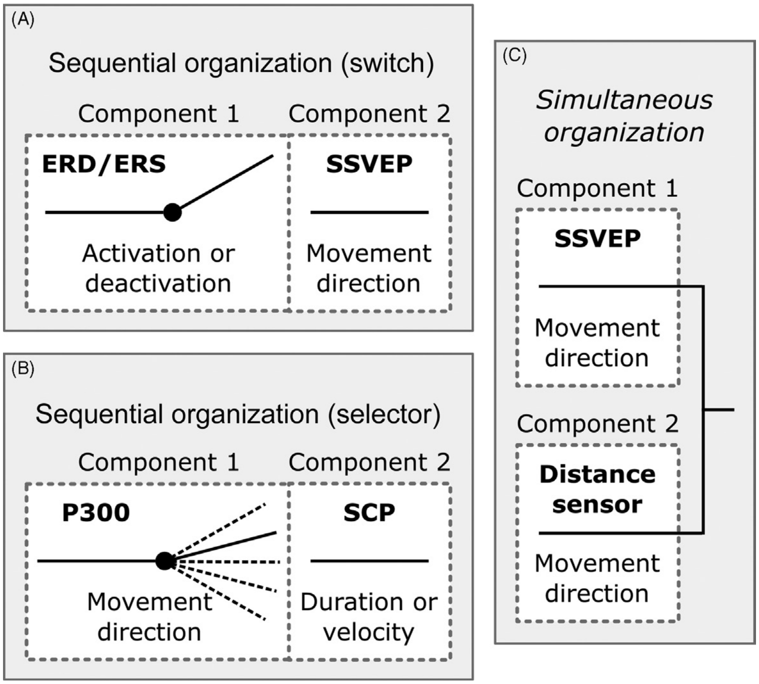

FIGURE 10.2

(A) EEG-based BCI components sequentially organized (A) as a "brain switch," (B) as a "brain selector," and (C) simultaneously organized as competitive or complementary outputs.

Feature-level fusion, in turn, leads the modalities to different processing pathways before the fusion of their extracted features (Fig. 10.3B). It is usually applied to features strongly correlated, coupled, or synchronized, such as EEG and fNIRS signals collected around one particular region. Although this level decreases the information details, it increases the robustness of the system. This fusion level sometimes requires a dataset dimensionality reduction due to the high amount of features from both merged techniques.

Moreover, decision-level fusion happens when signals are individually processed and classified before their fusion, as shown in Fig. 10.3C. Such a fusion scheme is useful for applications with neural signals mixed with nonphysiological signals. For example, if the movement of a wheelchair is based on an SSVEP menu, the neural signal might select an option, and a distance sensor might correct the trajectory based on obstacles positions, as shown in Fig. 10.2C. Finally, semantic-level fusion occurs when different signals can each control separate tasks working together toward the same high-level task (Fig. 10.3D). An example is when two different mental tasks control forward/backward and right/left wheelchair movements, respectively.

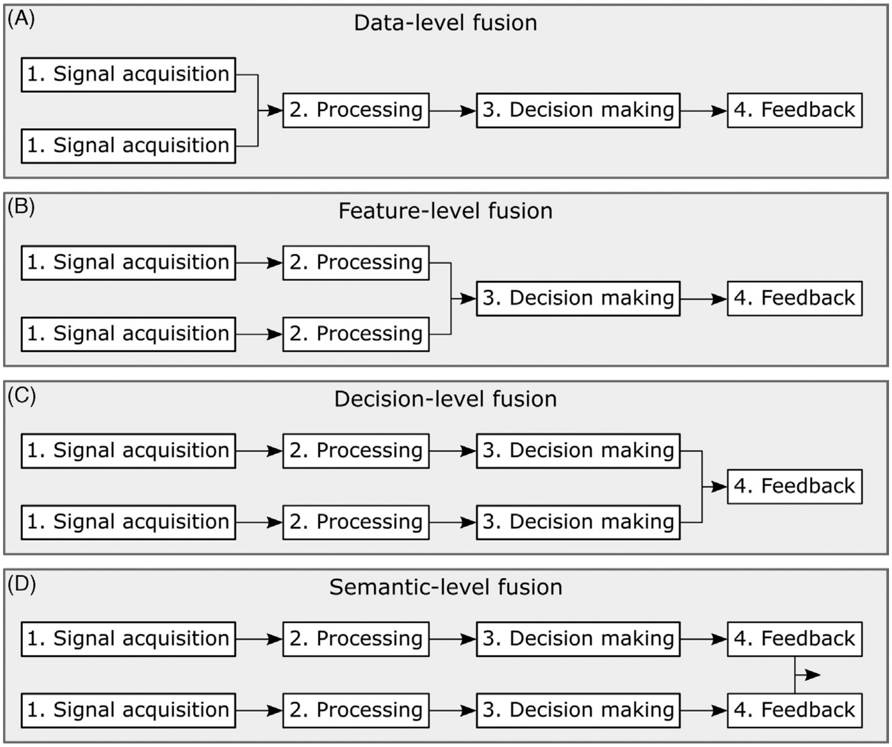

FIGURE 10.3

Example of fusion strategies at the (A) data, (B) feature, (C) decision, and (D) semantic levels.

10.2 APPLIED HYBRID BCIs

Considering the vast range of studies using brain–computer interfaces, the use of hybrid approaches occurs in an attempt to improve classification accuracy, the number of output options, to reduce the BCI illiteracy and the level of workload demanded to control the system, or even to create a switch-based system to allow the user to turn off the hBCI control during idle moments (Choi et al., 2017). In this context, Allison et al. (2010) merged ERD features related to left and right-hand motor imagery with SSVEP elicited by flickering LEDs in the corresponding side. The results showed improved classification accuracy and a decrease in illiteracy and workload. Similarly, Li et al. (2014) improved the number of control options combining ERD/ERS with SSVEP patterns and compared to the performances using each technique independently. Subjects were able to finish a circuit task faster and safer when using the hBCI approach. Furthermore, studies, such as Yin et al. (2015a) combine different brain imaging techniques (EEG and fNIRS) to improve performance based on the advantages of both methods.

A critical factor in selecting modalities to configure an hBCI setup is its final application. For example, final applications demanding several input options, such as spellers, cannot be operated by neural responses with little variability, such as SCP standards, while systems based on middle to high frequency neural responses, such as SSVEP, should not be recorded with low-sampling rate systems, such as fNIRS or fMRI. Based on the range of applications found in the literature, the recent review of Banville and Falk (2016) listed seven major application areas for hBCI studies: assistive technology and rehabilitation, spelling, graphical user interface (GUI) control, affective monitoring, decision aid system, games, and navigation.

Assistive technology and rehabilitation applications usually apply an hBCI to switch on/off (Pfurtscheller et al., 2010b; Scherer et al., 2007), to increase the number of movements available (Horki et al., 2011), or to redundantly select the movement (Lorenz et al., 2014) of a prosthesis and orthosis. Otherwise, rehabilitation tools usually focusing on neuromotor recovery tend to use neural responses related to motor processing, associated with muscular contraction (EMG) (Leeb et al., 2011) or even movement execution records (Rohm et al., 2013; Zimmermann et al., 2013). Applications, such as consciousness monitoring and spelling targeted at or evaluated on disabled individuals (Pan et al., 2014; Perdikis et al., 2014; Rutkowski and Mori, 2015; Spüler et al., 2012), should explore predominantly different modalities of neural signals, as other physiological signals would likely be hard or impossible to be voluntarily controlled by the user.

Studies focusing on spelling devices usually present a significant number of inputs (at least 36 commands, corresponding to different characters) and the modalities choice focus on precise identification of the target selection. One of the most common approaches is the combination of SSVEP and P300 stimuli. Studies use this to split sets of stimuli (helping to identify which part of the screen the user is focusing) or preselecting and expanding subgroups of characters, or even using both stimuli redundantly (waiting for both neural responses to identify a selection) (Chang et al., 2016; Panicker et al., 2011; Xu et al., 2013; Yin et al., 2013, 2014, 2015b). Other strategies include the comparison of the selected character with tracked eye movements (Choi et al., 2013; Lim et al., 2015; Yong et al., 2011; Zander et al., 2010) and the use of a passive validation caused by ErrP (Combaz et al., 2012; Zeyl et al., 2016a,b).

Considering GUI control, hBCIs merging P300 and MI tasks are applied to control a cursor (Bai et al., 2015; Li et al., 2010; Yu et al., 2012), a web browser (Long et al., 2012c), and an email client system (Yu et al., 2013). Other solutions use a larger number of combined modalities, with SSVEP and ERD/ERS neural responses associated with eye tracking and environmental camera monitoring to control a GUI, without the need for hand movements (Malechka et al., 2015). In turn, affective monitoring and decision aid system applications should consider not only neural signals but also other peripheral measures related to affective processing and decision making, such as heart rate, SCR, and eye tracking (Qian et al., 2009; Rutkowski et al., 2011). Otherwise, game applied hBCIs combine neural signals between them (e.g., SCP and SSVEP) (Mühl et al., 2010) or with different inputs, such as motor execution and virtual reality (Leeb et al., 2013) or joystick control (Kreilinger et al., 2011) data.

Finally, navigation applications include the control of an avatar or vehicle inside a virtual reality environment, with purely EEG-based hBCIs (Su et al., 2011) or combinations with eye-tracking systems (Jangraw et al., 2014; Lee et al., 2010). The control of robots has also been reported based on two (e.g., P300 and ErrP) (Bhattacharyya et al., 2014) or three (e.g., P300, SSVEP, and ERD) (Choi and Jo, 2013) neural responses, or mixing a neural response with EMG (Carlson et al., 2013) or EOG (Ma et al., 2015) signals. Kim et al. (2014), in turn, controlled a quadcopter along an obstacle course with mental concentration and eye-tracking records.

Another popular application in the navigation area is the control of wheelchairs (Fernández-Rodríguez et al., 2016), because the BCI may be a viable alternative providing users who are not able to control a wheelchair using a joystick with some independence (Kaufmann et al., 2014). The first hBCI used for wheelchair control relied on ERD/ERS patterns for fast-stop movements post-P300 detection. The response time with the hBCI was similar to that achieved with a sole P300-based BCI menu. Notwithstanding, when controlled exclusively by the P300 BCI, the wheelchair presented an average false stop every 30 s, while no false-stops were obtained with the hybrid approach (Rebsamen et al., 2008). Subsequently, several articles used hBCI for wheelchair control, as summarized in Table 10.2 and illustrated in Fig. 10.4.

As can be seen from Table 10.2, EEG is the brain imaging modality used in all reported experiments proposing BCI-based control of wheelchairs. Some aspects justify this predominance, such as the portability and wireless capability of existing EEG systems (Kranczioch et al., 2014), as well as the improvement of dry and active electrodes, which speed up the setup preparation (Lopez-Gordo et al., 2014). Also, wheelchair driving requires quick responses to avoid collisions or dangerous movements. Thus, the temporal resolution of the EEG provides the best option, because some patterns related to neural responses can be identified at the millisecond resolution (Min et al., 2010).

Several studies used pure hBCIs, combining exclusively neural responses to control the wheelchair. Li et al. (2013b) developed a system to control the stop and go of wheelchairs. For this purpose, each option was comprised of a set of circles with one large button in the center illuminated to produce a P300 response, whereas eight surrounding smaller buttons flashed on the same frequency (e.g., 7.5 Hz) to provide an SSVEP response. Thus, when the subject focused on one option, both responses were recorded and the command executed. Volunteers were able to operate the wheelchair with response times between 4 and 5.5 s, in addition to reducing the number of errors to only one false positive per minute. Another common strategy is the use of motor imagination to control the movement direction, while attentional responses, such as P300 (Long et al., 2012a,b) or SSVEP (Li et al., 2014) are used to control acceleration and deceleration of the wheelchair. With these direction–velocity methods, subjects were able to complete both simple and complex circuits without colliding with obstacles (Cao et al., 2014), and requiring less time to complete the course compared to the experiments using a conventional BCI technique (Li et al., 2014).

Table 10.2 Studies About HBCI Control Applied to Wheelchairs and Key Features of Each Setup

Study	Modalities	Neural Task	Interaction	Fusion Level	Environment
Rebsamen et al. (2008)	EEG	P300 + MI	Sequential	Semantic-level	Real
Iturrate et al. (2009)	EEG + navigation sensors	P300	Sequential	Semantic-level	Simulated + real
Lin et al. (2012)	EEG + navigation sensors	Nonspecified	Simultaneous	Decision-level	Real
Long et al. (2012a)	EEG	MI + P300	Simultaneous	Semantic-level	Simulated
Long et al. (2012b)	EEG	MI + P300	Simultaneous	Semantic-level	Simulated + real
Puanhvuan and Wongsawat (2012)	EEG + EOG + navigation sensors	P300	Sequential and simultaneous	Semantic-level	Real
Carlson and Millán (2013)	EEG + navigation sensors	MI	Simultaneous	Decision-level	Real
Li et al. (2013a)	EEG + EMG	MI	Simultaneous	Data-level	Real
Li et al. (2013b)	EEG	P300 + SSVEP	Simultaneous	Decision-level	Real
Punsawad and Wongsawat (2013)	EEG + navigation sensors	SSVEP + MS + spontaneous alpha	Sequential and simultaneous	Semantic-level	Real
Cao et al. (2014)	EEG	MI + SSVEP	Sequential and simultaneous	Decision-level	Simulated + real
Li et al. (2014)	EEG	MI + SSVEP	Simultaneous	Semantic-level	Real
Wang et al. (2014)	EEG + EOG	MI + P300	Sequential and simultaneous	Decision-level	Real
Lopes et al. (2016)	EEG + navigation sensors	P300	Simultaneous	Decision-level	Real

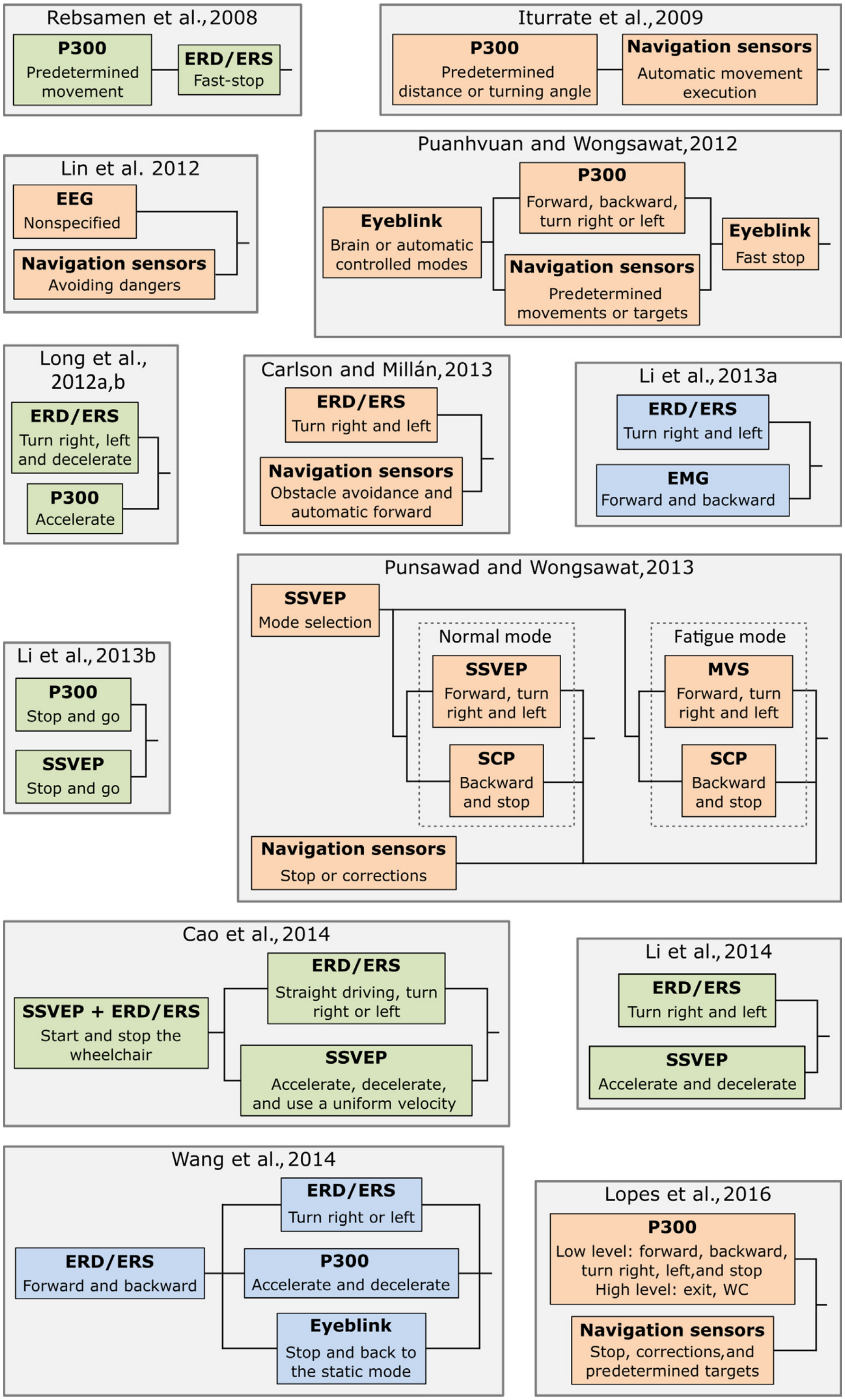

FIGURE 10.4 Summary of Hybrid BCI Approaches Used to Control Smart Wheelchairs.

Pure hBCI are represented in Light gray (green in Web versions), physiological hBCI in Dark gray (blue in Web versions), and mixed hBCI in black (red in Web versions).

Also, the combination of mental tasks can also be used as a system switch, as in the case of Cao et al. (2014) where MI and SSVEP were used together to turn on or off the wheelchair control (Fig. 10.4). A reasonable explanation for the use of two tasks composing the switch is the reduction of sensitivity to errors that could turn the system on or off at inappropriate times.

However, even with the small (or nonexistent) number of collisions recorded in different experiments, several studies used mixed hBCI systems to associate neural responses with the measurements of wheelchair positioning and navigation sensors, such as wheel encoders (Carlson and Millán, 2013; Puanhvuan and Wongsawat, 2012), laser sensors (Iturrate et al. 2009; Lin et al., 2012; Lopes et al., 2016), sonar sensors (Carlson and Millán, 2013; Punsawad and Wongsawat, 2013), or stereoscopic cameras (Lin et al., 2012). The inputs of these sensors can be used to make small corrections of trajectory, while the subject controls the chair, or to stop an ongoing movement if the subject fails to do so (Lin et al., 2012; Lopes et al., 2016; Punsawad and Wongsawat, 2013). Another approach is the use of these sensors to perform predetermined movements chosen by the volunteer using an attentional task (e.g., P300 or SSVEP) (Iturrate et al. 2009; Lopes et al., 2016; Puanhvuan and Wongsawat, 2012). Additionally, Carlson and Millán (2013) used navigation sensors to keep the wheelchair moving forward, while the user controlled another degree of freedom, such as turn right or left, with motor imagination patterns of the corresponding hands.

Finally, some groups used other physiological signals to improve the system setup. Li et al. (2013a) combined left and right MI tasks to turn the wheelchair to the corresponding side, while EMG signals from left and right teeth gritting were used for forward or backward movement control, respectively. In the absence of stimuli, the wheelchair was set to stop. Wang et al. (2014) in turn, used three different tasks to control the movements of the wheelchair. First, during static mode (with the wheelchair stopped), ERS/ERD patterns were used to start moving forward or backward. After, ERD/ERS patterns we used to turn left or right, P300 patterns to accelerate and decelerate, while eye blinks were used to stop the wheelchair and set it back to static mode. The same strategy of using eye blinks to change the operation mode were employed by Puanhvuan and Wongsawat (2012), to select between the use of brain signals (choosing movements from a P300 menu) to control the wheelchair or to keep its control in automatic mode (using wheelchair decoders to set the movement). Eye blinks were also used to fast stop any action.

10.3 IS MORE ALWAYS THE MERRIER?

An assistive technology based on BCIs should remain operable throughout the day, with minimal need for maintenance, which is still impractical even with conventional BCI systems (Müller-Putz et al., 2012). Moreover, the BCI design also should consider issues, such as personal needs, availabilities, and constraints, which if not done accurately, could lead to device abandonment (Müller-Putz et al., 2015).

Considering all these points, Nijholt et al. (2011) listed the top seven problems that impede wider usage of present BCI systems for end users, namely: reliability, proficiency, bandwidth, utility, convenience, support, and training. Some of these aspects were improved with hBCI approaches; however, each solution should be optimized and integrated into a single system in order to become relevant for real users (Müller-Putz et al., 2012). Each of these problems is discussed next.

Reliability: considering real world applications, quotidian aspects play a crucial detrimental role in BCI performance. For example, users present mental and physical fatigue throughout the day, as well as varying neural responses, which can vary within and across days, biological or environmental noise (Falk et al., 2011). Finally, neural patterns or physical movements the user cannot control will decrease the signal-to-noise ratio (e.g., stress, negative or positive emotions, spasms and movements, and fasciculation.) (Nijholt et al., 2011).

In this context, the use of simultaneous hBCI allows the improvement and maintenance of general accuracy when individual aspects of each subject are considered (Amiri et al., 2013). For example, the use of body and mind monitoring systems in parallel with the neural inputs of BCI provides information about fatigue, tiredness, and stress, as well as tools for signal quality evaluations (e.g., eye movement and muscular artifacts in EEG signals using EOG and EMG, respectively, or heart rate artifacts in fNIRS using ECG) (Müller-Putz et al., 2011) and the environment (Falk et al., 2011). Otherwise, mental fatigue and workload can be reduced using a brain switch to turn off the BCI system during idle periods, also reducing false-positive results and improving the overall accuracy (Banville and Falk, 2016). Control stability can also be monitored using ErrP responses to identify possible mistakes and missed selections (Combaz et al., 2012). Thus, hBCI opens the doors for adaptive systems capable of dynamically re-estimating the statistical properties of the BCI algorithm, for example, changing the classification weights of channels and measures, and achieving optimal solutions to daily signal changes (Amiri et al., 2013; Müller-Putz et al., 2011, 2015).

Proficiency: as described previously, no existing BCI approach works accurately across all (many) users (Nijholt et al., 2011). This is due to intersubject brain structure differences, which make specific neural responses hard to measure on the scalp, even after extensive training or improved signal processing methods (Allison and Neuper, 2010).

An alternative solution to this so-called illiteracy problem is the increase of system robustness using redundant inputs. For example, the use of different neural patterns to accelerate/decelerate the wheelchair, or the combination of different neuroimaging modalities to control the movement direction. The use of complementary inputs can improve the chances of the BCI algorithm to understand the user intention since only one pattern/modality cannot be sufficient for a particular subject (Choi et al., 2017). With this in mind, comparing subject illiteracy using ERD, SSVEP, and ERD + SSVEP setups, some studies found a significant number of illiterate subjects to standard BCI becoming literates to the hBCI approach (Allison et al., 2010; Pfurtscheller et al., 2010a). Moreover, questionnaire results showed no difference in the difficulty or workload reported by participants during hBCI tasks compared to conventional BCI (Allison et al., 2010; Zander et al., 2010). However, mental task collisions are still an open question for BCI researchers since diversified results were found recently. Lorenz et al. (2014) compared ERP-ERP, ERP-MI, and MI-ERP sequential combinations, finding similar accuracies and usability for the first two pairs, while the MI-ERP testes reached much worse results. Brunner et al. (2010, 2011) described that adding SSVEP to ERD signals degraded the ERD classification accuracy while adding ERD to SSVEP did not effect the SSVEP detection. However, several other studies did not find significant differences in classification accuracy when combining activities or modalities (Leeb et al., 2013; Panicker et al., 2011; Su et al., 2011).

Bandwidth: although some BCI applications attained information transfer rates (ITR) 60–100 bits/min, this is still slower compared to other communication systems (Nijholt et al., 2011). As expected, some hBCI systems can lead to even worse ITR due to the addition of one step (e.g., with a brain switch), the combination of low sampling rate modalities (e.g., fMRI), or a slower neural response (e.g., hemodynamic response) (Banville and Falk, 2016). In contrast, hBCIs allow different strategies to improve ITR, such as to adaptively switch between more reliable modalities, select the first occurrence of two possible neural responses, or even reduce the number and length of analysis windows and correct unwanted selections with ErrP. In this context, several studies reported higher information transfer rates using hBCIs compared to control protocols (Cao et al., 2014; Postelnicu and Talaba, 2013; Spüler et al., 2012; Tomita et al., 2014; Xu et al., 2013; Yin et al., 2013, 2014). For example, SSVEP + P300 spellers presented ITRs higher than 50 bits/min including the interval between selections and possible corrections (Yin et al., 2014), with subjects reaching more than 1 bit/s in some experiments (Yin et al., 2013). Finally, wheelchair studies reported participants reaching 295 bits/min ITR during direction and speed control using an MI + SSVEP hBCI (Cao et al., 2014).

Utility: current applications of BCIs are usually focusing on only one task (e.g., spellers, wheelchair controls), while real applications should be able to help different aspects of the user's life, and change between these tasks with minimal delay or hassle (Nijholt et al., 2011).

One advantage of hBCIs is the sequential organization of complex tasks or applications in different steps (Amiri et al., 2013). Moreover, setting a brain selector with various applications as options, end users will be able to choose between different functions to use at each moment or even more than one application at the same time. It will also be possible to change between neuroimaging modalities to select the one that allows better control for the desired application (Banville and Falk, 2016). Shared control systems are also of great interest to the hBCI field since it allows input signals from the final application (e.g., prosthesis, wheelchair) and improve the final control accuracy and utility (Müller-Putz et al., 2015). It will allow, for example, setting the wheelchair control automatically while the user focuses his attention on the speller application. For now, users are already allowed to drive a wheelchair manually or automatically (Puanhvuan and Wongsawat, 2012), while other studies also include a robotic arm to the wheelchair setup (Palankar et al., 2009; Pathirage et al., 2013). More recently, Obeidat et al. (2017) tested the user experience with a portable P300 speller (implemented using a mobile phone) in a moving wheelchair, evaluating the effect of screen size, environmental distractors, and muscular artifacts due to head stabilization. They found performances similar to monitor screen experiments, inferring the low effect of distractors and muscular noise, in addition to high scores for comfort and alertness and low scores of fatigue (Obeidat et al., 2017). These results demonstrate, for instance, that the use of hBCI is plausible for multiple applications associated with the control of wheelchairs.

Convenience: a typical BCI setup usually takes at least 20 min of preparation before usage and often requires the use of conductive gels which also demands a cleaning process after the experiment (Nijholt et al., 2011). In this sense, one expected problem concerning hBCIs is the increased difficulty to set up the system, considering the addition of different modalities with different preparation procedures (Amiri et al., 2013). However, as previously mentioned, recent EEG setups have benefited from the development and advancement of dry and active electrodes, which speed up the preparation procedure for BCI experiments (Lopez-Gordo et al., 2014). Moreover, some studies have demonstrated that only two pairs of electrodes are enough to create an ERD + SSVEP hBCI to realize orthosis control (Pfurtscheller et al., 2010a), thus improving convenience. Other modalities used in hBCIs have also benefited by the evolution of wearable devices, such as heart rate monitors, smart watches, tracking devices, and smart glasses (Mukhopadhyay, 2015), which can improve hBCI convenience. However, even with the improvement of available technologies, disabled users still need help with setting up conventional or hybrid, which leads to the two problems described next.

Support: a final user of a BCI system, especially patients and users with motor restrictions, will probably have difficulties with system usage. He or she will need help to choose, buy, configure, prepare, maintain, repair, upgrade the system, or even during the training process (Nijholt et al., 2011). One possible solution to this problem is an hBCI based on different EEG responses with a portable, plug-and-play system with little or no need of maintenance, similar to the one of Thompson et al. (2014). Considering a scenario with end-users, a caregiver or even a paraplegic user might easily configure the setup at the beginning of the morning allowing its usage along the day. Permanent solutions, eliminating the need for external assistance or the daily configuration of the recording system tend to involve invasive modalities, such as ECoG (Schalk and Leuthardt, 2011) or even the use of deep brain stimulation electrodes (Benabid et al., 2011). However, besides the risk factors associated with the surgical procedure and the rejection of the implants, considering wheelchair applications the user would still not be entirely independent since he would require assistance to get on and off the wheelchair.

Training: many BCI techniques require extended periods of training, which can be tedious, repetitive, and without progress during the sessions. This aspect may become a discouraging factor to the end user of the system (Nijholt et al., 2011). Along this vein, hBCIs tend to be more complex than common BCI approaches, thus can lead to more tiring and stressful training for users (Amiri et al., 2013). Some alternatives to reduce the training and calibration demand have been explored, such as the use of intersubject databases (Abibullaev et al., 2013), transfer learning (Verhoeven et al., 2016), unsupervised learning systems (Lu et al., 2009), or even the generation of artificial EEG signals based on a few trials to compose the training set (Lotte, 2015). However, although these approaches are prominent to solve the training problem, they are in embryonic stages and open research opportunities for future exploration.

As shown, multimodal and hybrid BCIs are helping to solve many current problems of traditional BCIs. In the future, it is expected that the best and most complete BCI system will be an hBCI. It will allow users to control external devices using mental tasks or signal modalities that are easiest, most comfortable, and most efficient for them (Nijholt et al., 2011). However, it is important to highlight that not all BCI strategies are equally useful. For example, if one mental task or imaging modality is not relevant to the desired context, it might lead to worse results than using a conventional BCI. Therefore, task and modality choices should be evaluated before the hybridization (Lorenz et al., 2014) and, in some cases, a BCI cannot be the best option (Pfurtscheller et al., 2010a).

10.4 EXISTING AND EMERGING TECHNOLOGIES

On October 2016, Switzerland received the first edition of the "Cybathlon," an international Olympic competition for parathletes using the most advanced assistive technologies developed to date (Riener and Seward, 2014). Unlike the Paralympic Games, where maximum physical athletic performance is evaluated, the Cybathlon had athletes rely on the most modern powered devices to compete across six tasks: a functional electrical stimulation (FES) bicycle race, a powered leg prosthesis race, a powered wheelchair race, a powered exoskeleton race, a powered arm prosthesis race, and a brain–computer interface race (Riener, 2016). The primary objective of the Cybathlon was to encourage teams (from academia or industry) to come up with innovative solutions to cope with day-to-day routine challenges (Riener, 2016; Riener and Seward, 2014).

Considering the next Cybathlon edition to be held in 2020, would it be possible for a team to compete in the powered wheelchairs race using an hBCI-controlled system? Moreover, knowing that Cybathlon rules allow for the use of commercial systems as components of the used equipment, how far would we be from building an hBCI system using only low-cost commercial models?

For the acquisition of neural signals, today EEG is the modality closest to offering equipment that is low cost and portable. In recent years, numerous low-cost mobile devices using dry electrodes have emerged in the marketplace, for example, MindWave Mobile (Neurosky, San Jose, USA), Emotiv EPOC (Emotiv Systems, San Francisco, USA), with prices ranging in the hundreds to thousands of dollars (compared to tens of thousands of dollars of conventional EEG equipment). Experiments comparing these systems with state of the art EEG amplifiers showed that although more susceptible to artifacts, and requiring significant corrections before analysis, the wireless mobile EEG performed as good as the wired laboratory EEG system in event-related paradigms (De Vos et al., 2014; Frey 2016a,b; Ries et al., 2014). However, although presenting promising results for oddball classification when used in indoor and outdoor environments (Debener et al., 2012), the low-cost mobile EEG must be utilized with caveats in the context of BCI (Carrino et al., 2012; Duvinage et al., 2013). However, although fNIRS is not yet low-cost equipment, wearable systems, such as the NIRSport (NIRx Medical Technologies, Berlin, Germany), present robust results recording different real life activities (Balardin et al., 2017) or performing mental state classification with environmental noise (Falk et al., 2011).

For physiological monitoring, the most widely accessible commercial tools are heart-rate (HR) monitors for sports. With values ranging from tens to hundreds of dollars, these systems are mobile and wearable and typically come in two different formats: chest belts (using ECG signals) or watches (using photoplethysmography signals). A comparative study showed a high correlation between the HR measurements made by photoplethysmography-based watches and laboratory ECG devices, mainly in moments of low physical activity or rest, which would be the condition of a wheelchair user (Jo et al., 2016). Similarly, a study comparing different HR monitors based on chest belts found reliable results among the various models, but pointed out that the choice of the best device depends on the usage purpose, location, and weather (Schönfelder et al., 2011). Moreover, many of these monitors are equipped with accelerometers of up to three dimensions, plus integrated GPS, such as the Garmin Forerunner (Olathe, USA), Tomtom Runner Cardio (Tomtom, Amsterdam, The Netherlands), and the Polar M series (Polar Electro Oy, Kempele, Finland). Such functionalities may open doors for movement detection and could result on, for example, the mapping of gestures (Wen et al., 2016; Xu et al., 2015) as complementary information for an hBCI system.

An emerging technology that can indeed be used in an hBCI setup is smart glasses, with models coupling different types of sensors. The most popular models, such as Google Glass (Google, Mountain View, USA) and Moverio BT-200 (Epson America, Long Beach, USA), have prices ranging from hundreds to thousands of dollars and are usually equipped with microphones and video cameras, allowing voice- or groan-based control (Mazo et al., 1995; Simpson and Levine, 2002), compass, accelerometers, and gyroscope sensors, allowing head motion based control (Pajkanović and Dokić, 2013; Rechy-Ramirez et al., 2012; Rofer et al., 2009), and a near-to-eye display placed on the lenses, which can be used in the future to present stimuli, for example. Recently, some studies have started to develop eye-tracking systems within smart glasses (Kocejko et al., 2015; Zhang et al., 2014). Future perspectives list various monitoring improvements to smart glasses, such as the inclusion of skin temperature sensors and EOG electrodes, or even acoustic and haptic feedback (Amft et al., 2015).

Another technology available, which is fundamental for a low-cost hBCI setup, is utilized by the smartphone and tablet. These devices allow for different wireless connections, such as WiFi and Bluetooth, and usually perform a good interface with low-cost EEG systems and sportive HR monitors previously mentioned (Cassani et al., 2015). Thus, different real-time monitoring systems are already available for outdoor experiments (Song et al., 2012; Stopczynski et al., 2014) and BCI apps/games (Wu et al., 2014). Moreover, smartphones and tablets also have at least two embedded cameras (front and rear), thus enabling eye tracking monitoring (Paletta et al., 2014) and face recognition (Kramer et al., 2010; Shen et al., 2014) as part of the hBCI. Importantly, stimuli in a P300 speller presented within a smartphone application showed satisfactory performance and usability even with the small size of the screen (Obeidat et al., 2017).

As can be seen, despite their inherent lower signal-to-noise ratios (compared to medical-grade equipment), several low-cost, mobile biomonitoring systems are readily available in the market today. As research into advanced signal processing techniques, machine learning tools (e.g., deep neural networks), and more robust hardware emerge, BCI applications will more and more come out of the lab and be explored in real-life environments. Within this context, competitions, such as the Cybathlon, are a great incentive to accelerate the advancement and combination of these technologies into hBCI systems.

10.5 FINAL CONSIDERATIONS

Hybridization is a relatively new concept in the field of BCI, showing promising results in different domains. The benefits of hBCI systems can be listed in three general ways (Müller-Putz et al., 2012): first, delivering to the user a higher number of different options and dimensions of control; second, being more intuitive and adaptive to user demands; and third, making BCIs practical for a wider variety of users. However, although hBCIs have shown vast improvements in these areas, it is currently most widely used in the laboratory, and a set of challenges still distance this field from its end users.

Future work should focus on tackling some key challenges of hBCI research, such as the identification of the best combination of modalities and tasks to achieve the best control of the desired goal (Pfurtscheller et al., 2010a). It also includes other related topics, such as the improvement of the signal to noise ratio of the input signals, the reduction of false positives and the adaptation to user states (e.g., fatigue) and environmental noise and distraction (Banville and Falk, 2016). Other open challenges to be investigated are the increase in the number of utilities, the reduction of illiteracy, and reduction of training duration (Nijholt et al., 2011).

For brain-controlled wheelchairs, developers should be aware that the combination of biomonitoring techniques can lead to increased power consumption and decreased durability of wheelchair batteries. Likewise, the size and weight of equipment should be considered so as to not interfere with wheelchair drivability and safety. In this context, the use of lightweight and compact equipment should be a consideration in the design of hBCI-controlled wheelchairs.

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