12
Hybrid Neurotechnology Systems

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12.1 Introduction

As described in the previous chapters of this book, two main groups of noninvasive brain imaging technologies are commonly used to compose a BCI system. The first and most popular is based on measurements of electrical or magnetic resultants from neural and synaptic activity, and includes methods such as electroencephalography (EEG) and magnetoencephalography (MEG). The high temporal resolution of these methods is fundamental to measure fast neural activities including event-related potentials (ERP), steady-state evoked potentials (SSEP), event-related desynchronization (ERD) or synchronization (ERS), as well as slow cortical potentials (SCP). For a complete overview related to these responses, please refer to chapter 2.

The second group includes functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and functional transcranial Doppler (fTCD). These methods measure relative changes in local blood oxygenation due to the metabolic activity of brain cells. This local blood oxygenation level-dependent (BOLD) change is commonly explored in experiments using fMRI, while fNIRS measures relative concentrations of oxyhemoglobin and deoxyhemoglobin (for a deeper discussion, please refer to chapters 4 and 5). Although hemodynamic-based methods usually present lower temporal resolution, they have higher spatial information that allows the selection of specific brain targets.

Hybrid BCI (hBCI) systems merge two or more monitoring methods (with at least one type of neural signal) to achieve an optimal BCI design.[1] More recently, hybrid systems have also included the combination of neuroimaging with neuromodulation, such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS),[2] with emerging applications in sleep enhancement and brain-to-brain interfacing.[3,4]

In this chapter, we discuss the rationale for using hybrid neurotechnology systems, introduce basic hybridization concepts, and conclude with a brief overview of current hybrid BCI applications.

12.2 The Rationale for Hybrid Systems

As detailed by Nijholt et al. (2011), seven critical points should be addressed in future setups to achieve an optimal BCI system.[5] Hybrid BCIs are useful across all points, as detailed below:

- **Reliability:** It is known that BCI accuracy varies with factors such as mental and physical fatigue. In this context, an hBCI can be used to monitor the user's cognitive states and adjust internal parameters accordingly. For example, monitoring peripheral information in parallel to the main BCI system would provide instant information about stress and fatigue.

- **Proficiency:** There is no BCI system based on a single modality that works properly for all users. An hBCI can help with this limitation, and thus if one modality does not recognize the desired command, the second modality could allow the volitional control of the BCI setup. Moreover, with an hBCI, one modality could be used to remove artifacts from the other and improve accuracy.
- **Bandwidth:** Conventional BCIs present information transfer rates (ITR) around 100 bits per second. An hBCI can be used to accelerate the ITR by selecting the first occurrence of two redundant neural responses or by correcting unwanted selections and constantly measuring error potentials.
- **Utility:** Many single-modality BCI applications target only one task (for example, wheelchair control). Using a sequential hBCI, the user could select between different imaging modalities and increase the number of tasks, consequently improving the final accuracy and utility. As an example, wheelchairs could also include a robotic arm or communication device controlled by the hBCI.
- **Convenience:** Traditionally, BCI systems rely on lengthy preparation times and laboratory setups. Despite requiring multiple modalities, hBCIs can be more convenient. For example, given the complementarity of measures, a few pairs of electrodes from different modalities may provide the same information as multiple electrodes from a single method. In fact, recent technological advances have allowed for the development of miniaturized hybrid EEG-fNIRS sensors.
- **Support:** Real-world BCIs should require low to no configuration, preparation, or maintenance. With an hBCI approach, different portable and plug-and-play devices working in parallel can be used as a backup system to reduce the maintenance frequency.
- **Training:** Training conventional BCIs can be tedious, repetitive, and without progress during the training sessions. Recent advances in subject-independent protocols or artificially generated training sets have shown to be valuable options to reduce the training duration of hBCIs. Also, studies applying hybrid approaches showed reduced training time compared to a single modality BCI.

12.3 Concepts of hybrid BCIs

An hBCI setup is characterized by the combination of different imaging modalities of brain tasks, the type of synchronization between modalities or tasks, and the level of fusion between the modalities or tasks. Given this number of options, the multimodal system should be carefully designed,[6] or the hBCI may underperform when compared to a single modality setup.[1]

12.3.1 Hybridization approaches

The most intuitive hBCI setup is to combine two or more streams of data-carrying neural activity. This approach is termed pure hBCI (Figure 12.1). It can be achieved by integrating multiple neuroimaging modalities[7] or merging multiple cognitive tasks from the same imaging method, for example, two different patterns from EEG.

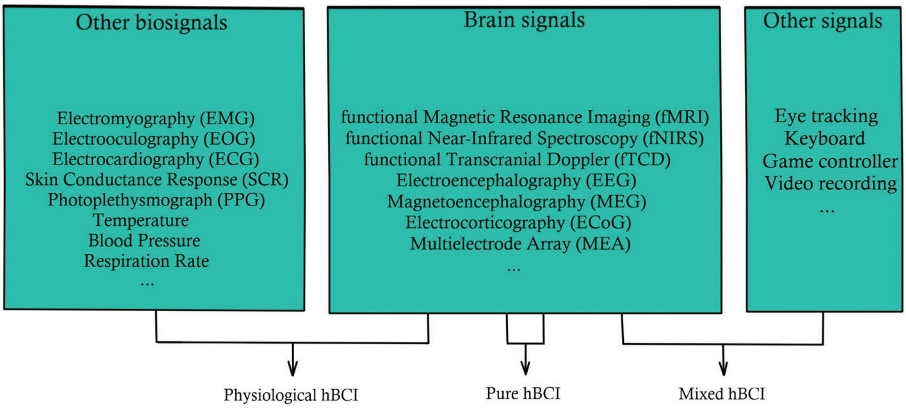

Figure 12.1 Different types of hybrid BCI, according to the combination of data modalities.

The use of other physiological signals in addition to neural data was proven a valuable addition to hBCI protocols.[8] Signals such as electromyography (EMG), electrooculography (EOG), electrocardiography (ECG), galvanic skin response (GSR), and blood pressure, among others, can provide valuable information about the participant's level of stress, attention, or affective responses.[9] The combination of neural data with other biosignals is termed physiological hBCI.[10] Lastly, non-physiological data can also be used to create an hBCI in a category named mixed hBCI.[20] This approach can include data from different equipment, such as a keyboard or an eye tracker to provide extra information to the hBCI setup.[11]

12.3.2 Synchronization

Given the possible combinations previously listed, an hBCI can also be categorized according to the synchronization between the chosen components. The first group includes approaches based on a sequential organization, in which two or more components work in series. As illustrated in figure 12.2, a possible implementation of this approach uses an initial element as a switch to activate or deactivate a second component.[12] Another implementation would use the first component as a selector to choose between two or more possible options, such as selecting different sets of movements in wheelchairs (e.g., moving straight or taking turns). The second group is composed of protocols in which its components work in parallel, adding complementary information about the desired effect. One example is the parallel combination of EEG and EMG techniques that can be alternated to reduce the influence of fatigue on control performance of either component.[13]

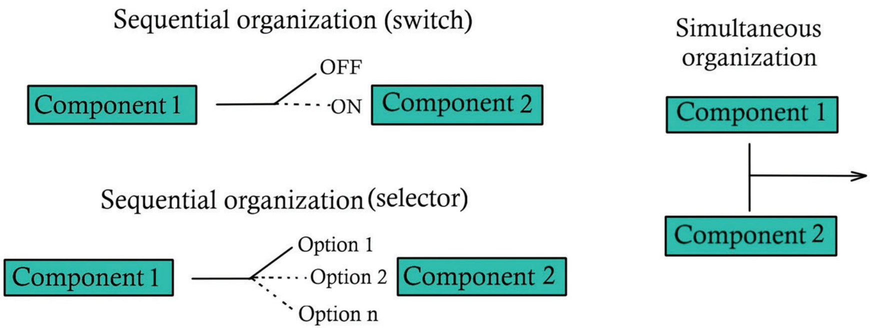

Figure 12.2 Examples of different synchronization between components.

12.3.3 Fusion levels

Every BCI system follows four main steps: data acquisition, preprocessing of the acquired information, decision making, and output presentation.[14] In an hBCI protocol, information fusion can occur at any one of these steps (Figure 12.3.), according to the components of the system.[15]

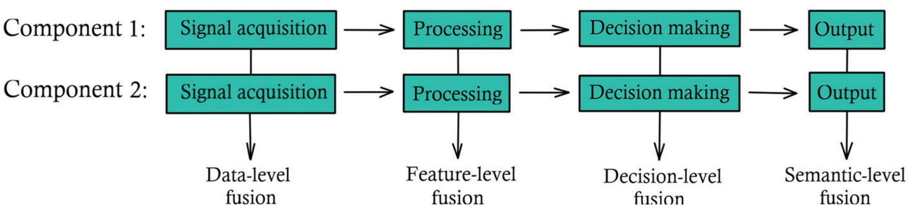

Figure 12.3 Example of fusion strategies in a sequential hBCI. Horizontal arrows represent the common BCI steps, while vertical arrows show the steps in which the different types of fusion occur.

Protocols merging unprocessed data are said to rely on data-level fusion. This approach is commonly employed by systems with components providing similar information or systems using one modality to improve the quality of a second one. For example, a common data fusion approach uses EMG or EOG signals to reduce noise in EEG data before feature extraction.[25]

Systems merging features from different components are said to perform feature-fusion level. This approach is popular for protocols combining data that requires separate processing pathways. One example is the extraction of features from EEG and fNIRS data separately, followed by combining these features as inputs for a classifier. Although higher robustness can be achieved, this fusion level usually presents higher dimensionality, which can harm performance when only a few data points are available.

Designs with decision-level fusion apply independent data processing methods and decision-making algorithms for each component before combining these labels. This structure is particularly useful for setups based on "voting algorithms," which combine the outputs from multiple classifiers as votes to reach a final decision. In a particular case of decision-level fusion, protocols combining modalities that control different outputs, but work together toward the same high-level task, are also said to use semantic-level fusion. This structure is typically used when combining neural data with non-physiological inputs.

12.4 Applications

This section briefly presents three promising application areas of hBCI systems: wheelchair control, speller and GUI control, and passive and affective BCIs. Additionally, we discuss the up-and-coming area of research on hybrid neurostimulation-neuroimaging systems.

12.4.1 Wheelchair control

A popular application of BCIs is the control of wheelchairs.[16] The first hBCI used for wheelchair control relied on detecting a P300 wave to select a destination in a predefined list and EEG-based changes in brain power for fast-stop movements.[17] Since EEGs can be portable and have high temporal resolution, they have been the most popular modality for wheelchair control,[18] with many applications relying on pure hBCI implementations, including the combination of visual P300 or motor imagery to control movement direction and steady-state-visually evoked potentials (SSVEPs)to control acceleration.[19,20,21]

Several studies have aimed at improving robustness by designing mixed hBCI systems based on the wheelchair's positioning and navigation sensors. The sensors' inputs can be used to correct the trajectory while the subject controls the chair (for example, using motor imagery to move left or right) or stop an ongoing movement if the subject fails to do so.[22,23,24,25,26,27] Physiological signals have also been used to improve wheelchair control with, for example, using EMG-measured teeth-gritting for forward or backward movement control[28] and eye blinks to stop the wheelchair.

12.4.2 Hybrid BCI Spellers and GUI control

BCI spellers allow spelling words and sentences based on brain activity and have the potential to give locked-in patients a way to communicate again. Studies focusing on spelling devices usually present a significant number of inputs (at least 36 commands, corresponding to different available characters). The high number of inputs thus requires modalities that can allow the precise selection of a target character out of many. One of the most common approaches to this challenge is the combination of SSVEP and P300 stimuli. Studies use this combination to split sets of stimuli (e.g., identifying on 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).[29,30,31,32] Other strategies include comparing the selected character with tracked eye movements;[33],[34] or adapting the classifier decision based on the detection of an error-related potential (ErrP).[35,36]

More generally speaking, the problem of controlling a computer interface (e.g., cursor, buttons, lists, etc.) is also an active area of BCI research. For instance, hBCIs merging P300 and motor imagery tasks were applied to control a cursor,[37,38] a web browser,[39] and an email client system.[40] Other solutions use a larger number of modalities, with SSVEP and ERD/ERS neural responses combined with eye-tracking and environmental camera monitoring to control a graphical user interface (GUI).[41]

12.4.3 Hybrid passive and affective BCIs

As opposed to using neural signatures to control a device (known as active BCI), passive BCIs can be used to monitor implicit mental states of the user, such as their affective state, so that their environment can be adapted accordingly. Many affective states take their roots in deeper brain regions, making it challenging to measure neurophysiological correlates of emotions with techniques such as EEG and fNIRS.[42] Emotions, however, are known to modulate other physiological signals, such as heart rate or breathing patterns.[43] This realization has opened doors for new passive hBCI applications.

Seminal work showed the usefulness of combining peripheral physiological signals to classify emotions in a single user.[44] More recently, a series of work on multimodal affective monitoring was sparked by the release of open-source datasets such as the DEAP dataset.[45] For instance, in Clerico et al., (2018),[46] new EEG and GSR amplitude modulation features and phase-amplitude coupling features were introduced. In Gupta et al., (2016),[47] the authors fused several features extracted from EEG, fNIRS, physiological signals (themselves derived from fNIRS) to predict the reported quality of experience of 21 subjects listening to synthetic speech. Emotions are often confounded by other factors, such as fatigue or physical activity. Parent et al., (2019)[48] addressed this by combining EEG and physiological signals to monitor stress under physical activity.

12.4.4 Combining neuroimaging and neurostimulation

In a recording and stimulation hybrid system, also known as brain state-dependent brain stimulation (BSDBS),[49] various roles can be played by both halves of the system. The imaging part (e.g., EEG or fNIRS) helps reduce the inter- and intra-subject variability inherent to applying neurostimulation: finding the right location, timing, and stimulation parameters are simplified by monitoring brain states in real-time. In turn, neurostimulation (e.g., TMS, tDCS) can evoke, interfere with, or modulate neuronal activity, allowing manipulations to shed light on brain function.[50] In some applications, it can also be a way to transmit information directly to one's brain.

A recent application that combines brain stimulation and neuroimaging is called Brain-to-Brain Interfacing (BTBI) where direct communication from an individual to another is made possible; to do so, a recording modality needs to detect the brain activity of a "sender" (using a BCI), while a stimulation modality is necessary for delivering the information to the brain of a "receiver."

One of the first implementations of a BTBI was demonstrated in rats using intracortical microelectrode arrays.[51] A system was presented that linked two rats kept separate in two different locations — an "encoder" rat and a "decoder" rat — tasked with pressing a lever as indicated by an LED. Using the encoder rat's somatosensory activity, information was sent to the decoder rat via electrical brain stimulation to motivate it to press the lever at the same time as the encoder rat; only then would both get rewards.

The first published account of BTBI involving humans was of an interface between a human and a rat.[13] In Yoo et al., (2013), a human used an SSVEP BCI to control the tail of an anesthetized rat through transcranial focused ultrasound (FUS), a non-invasive stimulation technique that induces brain activation electromechanically (see di Biase et al., [2019][52] for an introduction).

Human-to-human BTBI was only reported in 2014 independently by two groups. In Grau et al., (2014),[54] a system combining a motor imagery BCI on a first individual and robotized TMS stimulation of the visual cortex of a second individual was presented. The "emitter" was then able to send bits (0 or 1) by performing motor imagery, which was relayed by email and used to control a TMS machine to induce phosphenes (a sensation of light in the visual field) in the "receiver." The BTBI was used to transmit the words "Hola" and "Ciao" from India-based emitters to France-based receivers.

In Rao et al., (2014),[53] motor imagery BCI and TMS stimulation were combined. This time, instead of using visual stimulation, the system directly induced a motor reaction in the receiver.[54] This communication channel was used in the context of a video game, where a first individual (the emitter) could see the current state of the game but not control it, whereas a second individual (the receiver) could not see the game but could actually control it.

More recently, Jiang et al., (2019) reported the use of both stimulation and recording modalities on a single individual in the context of a multi-person BTBI.[55] Their approach combined two senders with SSVEP BCIs and one receiver with TMS and an SSVEP BCI in a Tetris-like game scenario. The two senders, who could see the game state, had to pick a move through their SSVEP BCI. Their suggestions were then sent to the receiver through occipital TMS, who had to decide, without seeing the game screen, how to rotate a game piece (done with an SSVEP BCI) based on the sender's suggestions.

12.5 Final considerations

In this chapter, we introduced the concepts of BCI hybridization and the rationale for using hybrid systems. We then briefly reviewed multiple applications based on hybrid systems in various areas, such as mobility, communication, and imaging-stimulation integration. Although hybridization opens the door to improved performance and new applications, the novelty of this field implies that research is still needed before hybrid systems are fully translatable to real-world contexts.

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