Hybrid Brain–Computer Interfaces and Their Applications

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Abstract

In the past decade, big progresses have been made in BCI studies. However, there have been a lot of challenges, including a low information transfer rate, multidimension/function control, man–machine adaptability, long-term robustness, and stability. In this chapter, we review the recent progress in hybrid brain–computer interface (BCIs; also called multimodal BCIs), which may provide potential solutions for addressing these challenges. In particular, four main classes of hybrid BCIs are introduced, including hybrid BCIs based on multibrain patterns, multisensory hybrid BCIs, hybrid BCIs based on multiple signals, and hybrid BCIs based on multiple intelligent techniques. We review state-of-the-art hybrid BCI systems by analyzing their general principles, paradigm, experimental results, advantages, and applications. We conclude that hybrid BCI techniques can be utilized to improve the target detection performance of BCIs and to perform multidimensional object control.
27.1 INTRODUCTION

Brain–computer interface (BCI) systems provide communication channels that allow brain messages to be conveyed to the periphery independent of the brain’s normal output pathway (Wolpaw et al. 2002). There are several techniques for measuring brain activities, which include near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electrocorticography (ECoG), and electroencephalography (EEG). EEG is one of the most commonly used modalities in BCIs because of its relatively low cost, its ability to capture near real-time responses, and its technical ease of acquiring signals. In this study, we primarily focus on EEG-based BCIs. The brain patterns used in EEG-based BCIs mainly include P300 potentials (Farwell and Donchin 1988), steady-state evoked potentials such as steady-state visual evoked potentials (SSVEPs) (Muller-Putz et al. 2006), and event-related desynchronization/synchronization (ERD/ERS) produced by motor imagery (MI) (Pfurtscheller and Lopes Da Silva 1999).

Conventional “simple” EEG-based BCIs generally rely on a single signal input (i.e., EEG) and a single brain pattern, such as P300 potentials, which are produced by stimuli applied to a single sensory modality (e.g., visual stimuli), while no other intelligent/automation techniques are incorporated into the system. The general architecture of a BCI system is shown in Figure 27.1, which includes four stages of brain signal processing: data acquisition, preprocessing, feature extraction, and translation algorithms. In the data acquisition, brain signals are first acquired using sensors. For example, the EEG measures signals acquired from electrodes placed on the scalp, as shown in Figure 27.1. In BCI signal processing, many signal components are noisy. Preprocessing methods such as spatial filtering and temporal filtering can improve signal quality by greatly reducing noise and artifacts. Then, useful signal features reflecting the user’s intent are then extracted from the preprocessed brain signals. For EEG-based BCIs, the selection of feature extraction methods depends on the brain patterns such as event-related potentials (ERPs), ERD, and ERS reflected by mu and beta rhythms. After the features that reflect the intentions of the user are extracted, the next step is to translate these features into device control commands, using a classification method, such as the Fisher linear discriminant (FLD), support vector machine (SVM), and Bayesian model (Li et al. 2009). Major progress has been made in the paradigm designs, brain signal processing algorithms, and control systems of such simple BCIs. However, these BCI systems are faced with several challenges, including a low information transfer rate (ITR), multidimension/function control, man–machine adaptability, long-term robustness, and stability.

FIGURE 27.1 Basic design and operation of a BCI system. (Modified from Li, Y., K. K. Ang, and C. Guan. 2009. Digital Signal Processing and Machine Learning.)
A potential solution to the above challenges is the use of a recently developed type of BCI, namely, hybrid BCIs. As described in Allison (2010), Allison et al. (2007), and Pfurtscheller et al. (2010a), a hybrid BCI is composed of a BCI system and an additional system, which might be a second BCI system, and is designed to perform specific goals better than conventional BCIs. Compared to a conventional BCI system (as shown in Figure 27.1), the signal flow of a hybrid BCI system can be described as follows. (1) In the signal acquisition, the signal input can be from multiple signals (e.g., EEG and NIRS), or multibrain patterns (e.g., P300 and SSVEP), which are evoked by multisensory stimuli (e.g., audio-visual stimuli). (2) In the signal processing, a hybrid BCI system can provide only a single output/control signal or multiple outputs/control signals. In the former case, when multiple brain patterns or multiple signals are involved, data fusion is generally required at the feature or decision level. In the latter case, the multiple control signals may be separately manipulated by the different brain patterns probed by the system, and the fusion of these brain patterns is generally not necessary. (3) In the BCI application, a BCI system can be combined with an intelligent device (e.g., an intelligent robot) to achieve shared control.

“Hybrid BCIs” and “multimodal BCIs” are two highly related concepts. In the literature (Li et al. 2016), researchers reported that “hybrid BCIs” and “multimodal BCIs” are interchangeable terms referring to the same definitions of BCIs. In the literature (Gürkök and Nijholt 2012), researchers described that multimodal BCI appeared mostly in the human–computer interaction and could be categorized as BCIs based on multimodal stimuli (also called BCIs in multimodal interaction) and BCIs based on multimodal signals (only refer to brain signals). Here, we further expand upon the definition of hybrid BCIs (Pfurtscheller et al. 2010a) or multimodal BCIs (Gürkök and Nijholt 2012). As shown in Figure 27.2, there are four main classes of hybrid BCIs.

1. Hybrid BCIs based on multibrain patterns, in which at least two brain patterns (e.g., P300 and SSVEP or MI and P300) are used. In this type of hybrid BCI, multiple brain patterns are evoked by single sensory stimulus.

2. Multisensory hybrid BCIs, in which brain patterns are evoked simultaneously by multisensory stimuli, such as audio-visual stimuli. In this class of hybrid BCIs, one or more brain patterns are evoked by multiple sensory stimuli.

3. Hybrid BCIs based on multiple signals, in which two or more input signals, such as EEG, MEG, fMRI, NRIS, electro-oculogram (EOG), or electromyogram (EMG), are combined in a hybrid BCI system.

4. Hybrid BCIs based on multiple intelligent techniques, in which the BCI is combined with another intelligent system to achieve shared control. Such combinations may lead to more reliable, flexible, usable, and powerful BCI systems by allowing subjects to focus their attention on a final target and to ignore low-level details related to the execution of an action (Brouwer et al. 2010).

The aim of this chapter is to introduce hybrid BCIs. The various classes of hybrid BCIs are explained in the following sections, beginning with general principles and designs and leading to their applications. Finally, concluding remarks and future perspectives are presented.

27.2 HYBRID BCIs BASED ON MULTIBRAIN PATTERNS

Hybrid BCIs combining multiple brain patterns, such as P300, SSVEP, and MI-based ERD/ERS, have been designed for various applications, such as spelling (Panicker et al. 2011; Xu et al. 2013; Yin et al. 2013, 2014), idle state detection (Li et al. 2013), orthosis (Horki et al. 2011; Pfurtscheller et al. 2010b), wheelchair navigation, and control of computer components, such as a two-dimensional (2D) cursor (Allison 2010; Li et al. 2010), mouse (Li et al. 2010; Long et al. 2012b), browser (Yu et al. 2012), explorer (Bai et al. 2015), or mail client (Yu et al. 2013). In the following section, we describe several P300-and-SSVEP–based BCIs, MI-and-SSVEP–based BCIs, and MI-and-P300–based BCIs.

27.2.1 P300-and-SSVEP–Based BCIs

Several P300-and-SSVEP–based BCIs have been proposed, such as for spelling (Panicker et al. 2011; Xu et al. 2013; Yin et al. 2013, 2014) and for toggling an on/off switch (Li et al. 2013). In these systems, SSVEP is a suitable candidate for incorporation into the P300 paradigm for two reasons. First, both P300 potentials and SSVEPs can be elicited by visual stimuli, allowing the subjects to simultaneously produce both brain patterns by simply performing a visual attention task without exerting extra mental load. Second, the P300 and SSVEP features are located in different domains (time domain vs. frequency domain), and the two brain patterns have significant independence. By utilizing both P300 and SSVEP features, hybrid P300-and-SSVEP–based BCIs can achieve better performance than conventional P300 or SSVEP BCIs, as described below.

27.2.1.1 P300-and-SSVEP–Based BCI Spellers

Recently, several studies have combined P300 and SSVEP to improve the conventional 6 × 6 BCI speller (Panicker et al. 2011; Xu et al. 2013; Yin et al. 2013, 2014). Generally, in these hybrid spellers, the P300 potential and SSVEP are elicited simultaneously by combining periodic flickers with random flashes. In a previous study (Panicker et al. 2011), an asynchronous hybrid BCI speller was proposed in which P300 potentials and SSVEP were combined to improve detection performance, as described below.

The graphic user interface (GUI) of the hybrid BCI speller in Panicker et al. (2011) comprised a 6 × 6 button matrix that contained 36 characters. The rows and columns flashed in orange in a random order to produce P300 potentials. At the same time, the buttons in the GUI flickered between white and black at 17.7 Hz to produce SSVEPs when the subject is focusing on a particular character. In this system, detection of the control state was performed through SSVEP detection, and recognition of the target button was carried out through P300 detection.

Detection of the P300 potentials and SSVEPs was performed separately (see the details in Panicker et al. 2011). For each round of intensifications for the rows and columns, SSVEP detection...
was performed. Specifically, the mean power values in a narrow and wide band were utilized to calculate a power ratio; the previously reported central frequency was 17.7 Hz, and the bandwidths were 0.6 and 4 Hz, respectively. When the power ratio exceeded a predefined threshold (i.e., 0.5 in Panicker et al. 2011), a control state was detected for this round; otherwise, an idle state was determined. If the control state was detected for at least three of five adjacent rounds, the subjects were expected to input a character, and P300 detection was performed, which included band-pass filtering, P300 feature extraction, and Bayes linear discriminant analysis (BLDA) or Fischer’s linear discriminant analysis (FLDA) classification. The target character was then determined according to the result of P300 detection.

In the online experiment, 10 healthy subjects underwent three experimental sessions that included 18 characters in each session. A character was identified and displayed on the screen once per presentation of five rounds, and the character was determined to be null if the control state was not detected. The experimental results demonstrated the effectiveness of this hybrid system, with an average control state detection accuracy of approximately 88%, an average P300 classification accuracy in the control state of 94.44%, and an average ITR of 19.05 bits/min.

27.2.1.2 P300-and-SSVEP–Based Brain Switch
In asynchronous brain switches, an important task is to distinguish the control and idle states based on the ongoing brain signals. Many studies have addressed the issue of asynchronous brain switches based on single brain pattern, such as SSVEP or MI. When designing the visual paradigm and the detection algorithm, we need to improve the accuracy of the control state detection (true-positive rate [TPR]) and reduce the false alarm rate (false-positive rate [FPR]) when the user is in the idle state.

In a study (Li et al. 2013), a hybrid BCI-based brain switch was proposed, in which P300 and SSVEP were combined to improve the performance of idle/control state detection. As shown in Figure 27.3, four groups of buttons are displayed on the GUI, and each group contains one large button in the center and eight small buttons surrounding it. All buttons in each of the four groups flicker at four different frequencies of 6.0, 6.67, 7.5, and 8.57 Hz, respectively, to evoke SSVEP. At the same time, the large buttons of the four groups are intensified in a random order through changing their shape and color to evoke P300 potentials. One group of buttons, for example, at the top, is set as a target for “on/off” command, and the other buttons are set as pseudo keys that do not activate any commands (the usefulness of pseudo keys were explained in detail in Pan et al. 2013). In the control state, the user can switch between “on” and “off” states of the system by focusing on the target and counting its flashes, whereas in the idle state, no particular button is attended to. The system detects the control/idle state by determining whether both P300 and SSVEP occur at the target.

The P300 and SSVEP detections were performed separately. In the asynchronous algorithm, the detection of P300, including low-pass filtering, P300 feature extraction, and SVM classification, was accomplished every 800 ms corresponding to one round of button flashes, and four SVM scores were obtained for the four button groups. The SSVEP detection, including band-pass filtering and power feature extraction, was performed every 200 ms, and four power ratios were computed for the four groups’ flickering frequencies. The decision was made every 200 ms. Specifically, summing the normalized P300 SVM scores and the normalized SSVEP power ratios, a detection index was obtained to discriminate the control and idle states. The detection of the control state was performed by judging whether any of two conditions was satisfied: (i) the difference of the detection index between target group and the other groups (pseudo keys) exceeds a predefined threshold; (ii) the target is recognized simultaneously by both P300 and SSVEP detection for a predefined number of consecutive times, for example, three times in Li et al. (2013). Two experiments involving eight subjects were conducted to validate the hybrid approach and system. For the purpose of comparison, three sessions were conducted in the first experiment for the hybrid P300-and-SSVEP–based BCI, a P300-based BCI, and an SSVEP-based BCI, respectively. It was shown that the performance of asynchronous control was better for a combined hybrid BCI than for the corresponding P300-only– or SSVEP-only–based brain switch. This improvement could be explained by the fusion of the
As an application, this hybrid brain switch was used to produce a “go/stop” command in real-time wheelchair control, where “go” and “stop” commands were always sent at the static and the in-motion conditions, respectively. A wheelchair control experiment involving five subjects was conducted. The subjects could send a “go” command in the static condition with an average response time (RT) of 4.21 s and an average false activation rate (FAR) of 0.48 events/min. In the in-motion condition, the subjects could send a “stop” command in an average RT of 5.50 s with an average FAR of 0.52 events/min.

**FIGURE 27.3** GUI of the hybrid brain switch combining the P300 and SSVEPs. (a) Each group of buttons flickers at a fixed frequency (6.0, 6.67, 7.5, or 8.57 Hz) by changing color between black and red. (b) Large buttons of the four groups are intensified with green squares in a random order, with each intensification lasting 100 ms with a 100-ms interval between two consecutive intensifications.
27.2.2 MI-and-SSVEP-Based BCIs

Several MI-and-SSVEP-based BCIs have been proposed for various applications, such as orthosis/artificial limb control (Horki et al. 2011; Pfurtscheller et al. 2010b) or MI training (Yu et al. 2015). In these systems, MI and SSVEP were combined such that MI induced the ERS/ERD and visual attention modulated the SSVEPs.

27.2.2.1 MI-and-SSVEP-Based Orthosis Control

MI- and SSVEP-based BCIs can be combined sequentially to reduce false activations during non-intentional control. Pfurtscheller et al. (2010b) proposed a hybrid MI-and-SSVEP BCI in which an MI-based brain switch was used to turn on/off an SSVEP-controlled orthosis. In this system, an SSVEP-based BCI was utilized to open the orthosis by gazing at an 8-Hz light-emitting diode (LED) and close the system by gazing at a 13-Hz LED. An MI-based brain switch was used to activate the SSVEP-based BCI only when orthosis control was needed and to deactivate the LEDs mounted on the orthosis during resting periods.

For the SSVEP-based BCI, the power density spectrum of the past 1-s EEG segment recorded from one bipolar channel was calculated every 250 ms based on a discrete Fourier transform. A weighted sum of each stimulation frequency and its second and third harmonics yielded the harmonic sum decision (HSD). The flickering light source with the highest HSD was selected if it was consecutively detected several times (see the details in Pfurtscheller et al. 2010b). For the MI-based brain switch, foot MI was detected from the “Cz” Laplacian EEG channel in a moving window of 1 s. From the training data (30 trials during MI and 30 trials during resting periods), the frequency bands with the most pronounced beta ERS were used to set up the FLDA classifier. The training of the FLDA classifier was performed based on a 10 × 10 cross-validation, and the classifier with the highest classification accuracy was used for online classification.

Six subjects participated in the experiment to control an electrical hand orthosis (see the details in Pfurtscheller et al. 2010b). For comparison, the orthosis was also operated using the SSVEP-based modality alone, without incorporation of the MI-based brain switch. Four of the six subjects succeeded in operating the asynchronous hybrid BCI with good performance (positive prediction value > 70%). The combination of these two BCI modalities, which are operated using different mental strategies, achieved much lower FPR during resting periods or breaks than the BCI based on SSVEP alone (FP = 1.46 ± 1.18 vs. 5.40 ± 0.90).

27.2.2.2 MI-and-SSVEP-Based MI Training

MI-induced ERD/ERS has been widely used in EEG-based BCIs. However, the differences in EEG between two MIs, such as left and hand MIs, are generally not sufficient to provide reliable control, especially for naïve subjects. It is believed that positive neuro-feedback can help subjects learn how to perform MIs to achieve effective BCI control. In one study (Yu et al. 2015), SSVEPs were combined with MI to provide positive feedback to facilitate MI training. SSVEPs are generally chosen as a supplementary tool for calculating feedback because (i) SSVEP- and MI-related brain patterns can be produced simultaneously; (ii) SSVEP is a type of evoked potential that can be stably detected in naïve subjects who have undergone little training; and (iii) SSVEPs can be detected based on a single trial of EEG data. This detection does not require an averaging procedure, as in ERP calculations. Therefore, the speed of detection of SSVEPs is comparable to that of MI, which is useful for providing real-time feedback.

The GUI contained a horizontal feedback bar in the center of the GUI, two SSVEP stimulus buttons (the two red arrows) presented on the left and right sides of the bar, and a cue arrow above the feedback bar that indicated the current task type. The flicker frequencies of these two buttons were 7.5 Hz (left) and 6.0 Hz (right). During training, the subjects were instructed to focus on the left or right flickering button to evoke SSVEPs as they performed left- or right-hand MI, respectively.
The algorithm of the hybrid BCI was based on hybrid features consisting of MI- and SSVEP-related brain signals. First, a common spatial pattern (CSP) algorithm is applied for MI discrimination, whereas a canonical correlation analysis (CCA) is employed for SSVEP detection. Then, the hybrid features are constructed by concatenating the CSP features and canonical correlation coefficients, which are then fed into an SVM classifier. Before training, a calibration data set is collected to update the classifier. The length of the feedback bar is determined according to the online classification results and is updated every 200 ms.

At the beginning of training, SSVEPs are more likely to dominate the feedback because (i) SSVEPs can be effectively evoked without requiring much training, and therefore, the SSVEP features are more discriminative than the MI features; and (ii) the classifier tends to automatically assign large weights to more discriminative features. Therefore, relatively accurate feedback is available at the beginning of training. However, as the training progresses, the subjects become more skilled in performing MI and, thus, gradually shift their attention to MI. In this case, the MI features become more discriminative and are automatically assigned higher weights in the SVM classification, whereas the SSVEP features deteriorate and become less dominant than at the beginning of training. Therefore, effective feedback is still available, where MI plays a more dominant role, and thus, MI training may be facilitated.

Twenty-four naïve subjects were randomly divided into two groups: one group participated in MI training based on hybrid feedback, and the other group, corresponding to a control group, participated in MI training based on the normal feedback of the MI features. The experimental results demonstrated that the subjects generated distinguishable brain patterns based on hand MI after only five hybrid feedback training sessions lasting approximately 1.5 h each. The subjects who received hybrid feedback significantly outperformed the subjects of the control group who received normal feedback. Moreover, as training proceeded, a shift of the corresponding classifier weights from SSVEP to MI features was observed. It was thus validated that the hybrid BCI system can be used to enhance MI training.

### 27.2.3 MI-and-P300–Based BCIs

An important aspect of EEG-based BCI systems is multidimensional control, which involves multiple independent control signals. These control signals may be obtained from multiple brain patterns, such as MI and P300 potentials. On one hand, P300 potentials represent a reliable type of brain pattern for generating discrete control output commands. On the other hand, MI-based ERD/ERS of BCIs is more efficient for producing continuous control commands. Recently, several studies have discussed multidimensional control based on MI-and-P300–based BCIs (Jennett and Plum 1972; Li et al. 2010; Long et al. 2012a,b; Rebsamen et al. 2008; Wang et al. 2014; Yu et al. 2013).

#### 27.2.3.1 An MI-and-P300–Based BCI Mouse

When using a BCI mouse, the user must sequentially perform two tasks. First, the user must move the cursor to a target on a monitor (termed 2D cursor control), and second, the user must click the target of interest (termed target selection). In this case, multiple control signals that can be generated by multiple brain patterns are essential.

Li and colleagues proposed a hybrid BCI combining MI brain patterns and P300 potentials for 2D cursor control (Li et al. 2010) and target selection (Long et al. 2012b). The GUI is shown in Figure 27.4, in which the circle and square represent the cursor and target, respectively, where the initial position of the cursor and the initial position and color (gray or dark gray) of the target are randomly provided. The three “up” buttons, three “down” buttons, and two “stop” buttons flash in a random order to evoke P300 potentials. The task of the subject is to move the cursor to the target and to then select or reject the gray/dark gray target. The control strategy of the user is described below. The user can move the cursor to the left or right by imagining his or her own left or right hand movement, respectively, and the user can move the cursor up or down by focusing on one of...
the three flashing “up” or “down” buttons to evoke P300 potentials. If the user does not intend to move the cursor in the vertical direction, then the user can focus on either of the two “stop” buttons.

To further implement a BCI mouse, target selection and rejection functions are required. Specifically, once the cursor hits the target of interest (gray square), the user can select the target by focusing attention on a flashing “stop” button and simultaneously maintaining an idle state of MI. If the target is not of interest (dark gray square), the user can reject it by continuing to imagine left or right hand movement without focusing on any flashing buttons.

The algorithm for the 2D cursor control includes two parts: P300 detection for vertical movement control and MI detection for horizontal movement control, with the details presented in Li (2010). The signal processing procedure for P300 detection consists of three stages: low-pass filtering, P300 feature extraction, and SVM classification. For MI detection, the signal processing stages include common average reference (CAR) spatial filtering, band-pass filtering of the specific mu rhythm band (8–13 Hz), feature extraction based on a CSP algorithm, and SVM classification.

The algorithm for target selection or rejection was based on the hybrid features of P300 potentials and MI, with the details presented in Long et al. (2012b). After extracting the features of the P300 potentials and MI using the same algorithms described above, a hybrid feature vector for each trial is constructed by concatenating the feature vector of the MI with the feature vector of the P300 potentials, which is then fed into the SVM for classification.

Eleven healthy subjects attended the online experiment, which included one session of 80 trials for each subject. Each trial included two sequential tasks. During the first task, subjects were instructed to move the cursor to a target that was presented at a randomized position on the screen. After the cursor hit the target, the subject was instructed to perform the second task of selecting or rejecting the target according to the color of the target (gray for selection and dark gray for
rejection). The time interval for the second task was set to 2 s. Among all subjects, the average time for one trial was 18.96 s, the average accuracy for successful trials was 92.84%, and the average for target selection accuracy given that the cursor was successfully moved to the target was 93.99%. Additionally, several data sets were also collected for offline analysis to demonstrate the advantage of P300 potential and MI hybrid features for target selection/rejection compared with use of P300 potential or MI features alone. The experimental results showed that the accuracy for use of the hybrid features was significantly higher than for use of only the MI or P300 potential features (hybrid features: 83.10 ± 2.12%; MI features: 71.68 ± 2.41%; P300 features: 80.44 ± 1.82%). This hybrid system offers three advantages. First, two independent control signals are generated based on MI and P300 potentials. Second, the user can move the cursor from an arbitrary position to a randomly positioned target. Third, this hybrid control strategy using the two modalities of MI and P300 potentials provides better discrimination performance than control strategies based on the use of MI or P300 potentials alone.

Based on the BCI mouse, several computer applications, including a BCI-based Internet browser (Yu et al. 2012), a BCI-based mail client (Yu et al. 2013), and a BCI-based file explorer, were implemented. In Yu et al. (2012), the authors proposed a BCI mouse-based web browser, in which common navigation functions are available, including traversing forward or backward through browsing history, selecting hyperlinks, scrolling through pages, and inputting text. Moreover, Yu et al. (2013) also proposed a hybrid BCI–based mail client that implemented electronic mail communication. Using this BCI mail client, the users are able to receive, read, write, and attach files to e-mails. Bai et al. (2015) proposed a hybrid BCI combining P300 and MI to operate an explorer. Using this system, users can access a computer and manipulate (open, close, copy, paste, and delete) files, such as documents, pictures, music, movies, and so on.

### 27.2.3.2 MI-and-P300–Based Wheelchair Control

Multiple control signals are also essential for the multidimensional control of a wheelchair. In a study, Long et al. (2012a) proposed a hybrid BCI paradigm based on MI and P300 potentials to provide directional (left or right) and speed control (acceleration and deceleration) commands to operate a real wheelchair.

The GUI is similar to that shown in Figure 27.4 for 2D cursor control except that no cursor or target is presented. In this hybrid BCI system, the user can control the left and right directions of the wheelchair via left- and right-hand imagery. For speed control, a hybrid paradigm is applied. For deceleration, the user must imagine a third motor event (e.g., movement of the foot) without paying attention to any of the flashing buttons. For acceleration, the user must pay attention to a specific flashing button without imagining any movement. Furthermore, the user can remain in an idle state to prevent activation of any commands.

The algorithm for wheelchair control includes two parts: the detection of directional control signals and the detection of speed control signals, and the details are presented in Long et al. (2012a). The algorithm first detects left or right MI for directional control. The direction detection module includes CAR spatial filtering, band-pass filtering, feature extraction based on a CSP algorithm, and linear discriminant analysis (LDA) classification. If no left or right MI is detected, no direction control is applied. Then, the algorithm performs speed control by discriminating among three states: foot imagery without P300 potentials (low speed), P300 potentials without foot imagery (high speed), and an idle state (no speed control). The speed detection module includes MI pattern extraction, P300 pattern extraction, and LDA classification.

To test the effectiveness of the control mechanism, two subjects were required to control a real wheelchair to follow a predefined route. In the experiment, each subject performed five trials. For each trial, the subjects were required to drive the wheelchair from the starting point to the end of the route (i.e., PL5) and then perform a “U” turn and drive the wheelchair back to the starting point. For the two subjects, the average distances driven while in low-speed and high-speed mode (path length) were 5.43 and 5.21 m, respectively. The average time for which the subjects operated the
wheelchair in the low- and high-speed modes were 45.38 and 20.14 s, respectively, of which the subjects incorrectly operated the wheelchair at high and low speeds in areas of the route that were designated as low- and high-speed areas for 4.54 and 4.1 s, respectively. In addition, no collisions occurred. These experimental results thus demonstrated that the two subjects could successfully control the wheelchair’s direction and velocity over the predefined route using the proposed hybrid BCI.

In this section, we described several hybrid BCIs based on multibrain patterns and presented several application systems. In fact, hybrid BCIs based on multiple brain patterns may be beneficial not only for normal subjects but also for BCI-illiterate subjects. Approximately 13% of healthy users are unable to effectively control simple BCIs based on P300 potential (Guger et al. 2009) or SSVEP (Allison et al. 2010b) brain patterns. Hybrid BCIs involving two or more brain patterns offer a possible solution for decreasing the number of users who are BCI-illiterate. For instance, a hybrid BCI combining MI and SSVEPs improved BCI performance in Allison et al. (2010a). The experimental results of 14 healthy subjects showed that the average accuracy of performing a task using the hybrid system was improved by approximately 6% compared to using conventional MI-only or SSVEP-only methods. Furthermore, there were no users who were unable to use the hybrid BCI, whereas there were five users who were unable to use the MI-only or SSVEP-only BCIs. This improvement in performance for hybrid systems may be due to the addition of a second task that provides more information to the classifier (Allison 2010).

Other hybrid BCIs based on multibrain patterns have also been reported. For instance, Allison et al. (2012) presented a new type of hybrid BCI based on MI and SSVEPs for continuous 2D cursor control. In this system, the users controlled the vertical movement of a virtual ball based on left- and right-hand MI while simultaneously controlling horizontal movement via SSVEP activity. The authors also developed a P300- and SSVEP-based hybrid BCI with a four-choice paradigm (Allison et al. 2014). The experimental results showed that the hybrid system led to improved detection performance compared to the SSVEP-only system, although the performance was not improved compared to the P300-only condition.

### 27.3 MULTISENSORY HYBRID BCIs

Humans possess multiple sensory pathways for processing information from the real world. This integration of multisensory stimuli is known to give rise to modulated ERPs, possibly through the strengthening of top-down attention (Stein and Stanford 2008). These enhanced effects of multisensory integration may be useful for improving the performance of BCI systems. Based on this consideration, several studies based on audio-visual (An et al. 2014; Belitski et al. 2011; Wang et al. 2015), audio-tactile (Rutkowski and Mori 2015; Yin et al. 2015), and visual-tactile BCIs (Brouwer et al. 2010; Thurlings et al. 2012) have been reported, in which bimodal stimuli are employed for improving system performance.

#### 27.3.1 AUDIO-VISUAL P300 BCIs

Recently, several studies based on audio-visual BCIs have been reported. An offline audio-visual P300-speller and the corresponding data analysis results were presented in Belitski et al. (2011), which showed that the strength of the P300 response was higher in audio-visual conditions than in visual-only or auditory-only conditions. An et al. explored a parallel speller for gaze-independent BCI in which the auditory and visual domains are independent from one another (An et al. 2014). Their results showed that 15 users could spell online with a mean accuracy of 87.7%. These existing results have shown that audio-visual integration could be a potential method to enhance brain patterns and to further improve BCI performance.

Wang et al. proposed a novel audio-visual BCI system in which spatially, temporally, and semantically congruent audio-visual stimuli based on numbers were employed (Wang et al. 2015). In the
GUI of this audio-visual BCI, there are two number buttons corresponding to two numbers randomly selected from 0 to 9 that are located on the left and right sides of the GUI, and two speakers are placed laterally to the monitor. The two buttons flash in an alternating manner. When a number button is visually intensified, the corresponding spoken number is presented from the ipsilateral speaker. In this way, the user is presented with temporally, spatially, and semantically congruent audio-visual stimuli that last for 300 ms, where the interstimulus interval (ISI) is randomized from 700 to 1500 ms.

Ten healthy subjects participated in the experiment, which consisted of three sessions that were administered in a random order. The sessions corresponded to the visual-only, auditory-only, and audio-visual conditions. In each session, the subject first performed a training run of 10 trials, followed by a test run of 30 trials. The online average accuracies across all healthy subjects were 95.67%, 86.33% and 62.33% for the audio-visual, visual-only and auditory-only sessions, respectively. The audio-visual BCI significantly outperformed the visual-only and auditory-only BCIs.

As shown in Figure 27.5, the ERP waveforms at the “Pz” electrode indicated that for the target stimuli, there were stronger P100, N200, and P300 responses in the audio-visual condition than in the visual-only and auditory-only conditions. As shown in Figure 27.6, there were more discriminative features for the audio-visual condition than for the visual-only and auditory-only conditions. The enhanced ERP components associated with the audio-visual stimuli, such as P100, N200, and P300, improved the performance of the audio-visual BCI system.

FIGURE 27.5 Average ERP waveforms from the “Pz” electrode for each stimulus condition among all subjects.

FIGURE 27.6 Point-wise running t tests were used to compare the target responses with the nontarget responses for the multisensory and unisensory stimulus conditions across all subjects for the 30 electrodes. Significant differences were plotted when data points met an alpha criterion of 0.05.
Hybrid Brain–Computer Interfaces and Their Applications

This audio-visual BCI system was applied to detect the awareness of patients with a disorder of consciousness (DOC). Currently, clinical diagnosis and awareness evaluations of patients with a DOC, such as patients in a vegetative state (VS) or a minimally conscious state (MCS), rely mainly on behavioral observation scales, such as the Coma Recovery Scale–Revised. There exists a high misdiagnosis rate (ranging from 37% to 43%) because these patients cannot provide sufficient behavioral responses. Detecting awareness in these patients is extremely challenging. Recently, the potential applications of BCIs in awareness detection and online communication for DOC patients have been explored in several studies (Coyle et al. 2012; Lulé et al. 2012). However, DOC patients with severe brain injuries have a much lower ability to use BCIs than healthy individuals. One possible solution is to apply the aforementioned audio-visual BCI to improve sensitivity in awareness detection. Seven patients with DOC performed a calibration run of 10 trials and a test run of 50 trials. Specifically, the test run contained five blocks, each of which was composed of 10 trials and was conducted on separate days because the patients became easily fatigued. Among the seven patients, the online accuracies for five patients (one VS and four MCS) were significantly higher than the chance level. For each of the five patients, the ERP waveforms measured at the “Fz” and “Oz” electrodes showed robust P300 responses elicited by the target stimuli. The results demonstrated the presence of command following and residual number recognition in the five DOC patients.

27.3.2 Audio-Tactile P300 BCIs

The aforementioned bimodal BCIs require visual interactions in terms of attending to stimuli and feedback, which limits their applicability to users with good visual acuity and intact gaze control. Because users require no visual interaction when operating auditory or tactile BCIs, auditory/tactile-based bimodal stimulus approaches may allow for visual saccade-independent BCIs. In a previous study, Yin et al. proposed a direction-congruent bimodal P300 BCI using the simultaneous presentation of auditory and tactile stimuli from the same spatial direction (Yin et al. 2015).

As shown in Figure 27.7, four selectable items were set up in the BCI system. The speakers and motors were placed at corresponding locations around the user such that the auditory-tactile stimuli from each speaker–motor pair represented one selectable item associated with a distinct spatial direction. Specifically, auditory stimuli were randomly delivered from one of four speakers, which played a short digital message in a female or male voice. Tactile stimuli were delivered in each target direction by two motors, oscillating between low- and high-power states to maximize tactile sensitivity. The bimodal stimulus duration was 200 ms, with an ISI of 200 ms. The users were

![Figure 27.7](image-url)
instructed to simultaneously focus their attention on the target stimulus according to the pre-trial auditory prompt while ignoring the stimuli from the other directions (nontargets).

Twelve healthy subjects participated in the experiments. Each subject took part in three sessions corresponding to bimodal auditory-tactile, auditory-only, and tactile-only conditions. Each session consisted of 15 runs, comprising a training phase and an online selection phase, with 150 selections in total. The experimental results showed that the bimodal approach achieved a higher average accuracy of 88.67% than the auditory (79.17%) and tactile (80.50%) approaches. Furthermore, the average ITR of the bimodal approach (10.77 bits/min) improved by 45.43% \((p < 0.05)\) compared to the auditory approach (7.41 bits/min) and by 51.05% \((p < 0.001)\) compared to the tactile approach (7.13 bits/min). These findings suggest that the proposed bimodal system is a promising practical visual saccade-independent P300 potential BCI.

Audio-tactile BCI study is still at the initial stages of research and development. For instance, Rutkowski and Mori reported a tactile and bone-conduction auditory BCI for vision- and hearing-impaired users (Rutkowski and Mori 2015). These existing results revealed several advantages of audio-tactile BCIs. First, the audio-tactile bimodal BCI yielded better overall system performance than both the auditory or tactile unimodal P300 BCIs. Second, audio-tactile BCIs offer the attractive possibility of targeting sensory domains that do not rely on visual stimuli to elicit potentials during visual computer applications, although the performances achieved using such systems are lower than the performances of gaze shift–dependent BCI systems. Third, audio-tactile BCIs represent an alternative type of BCI for users suffering from impaired vision.

In this section, we reviewed several promising multisensory hybrid BCIs, including audio-visual P300 BCIs and audio-tactile P300 BCIs. Initial results regarding visual-tactile BCIs have also been reported (Brouwer et al. 2010; Thurlings et al. 2012). For instance, Thurlings et al. investigated the effects of bimodal visual-tactile stimuli presentation on ERP components and discovered enhanced early components (N1) that may improve BCI performance (Thurlings et al. 2012).

### 27.4 HYBRID BCIs BASED ON MULTIPLE SIGNALS

To establish a hybrid BCI system, multiple signals can be used, including EEG, MEG, fMRI, EOG, NIRIS, and EMG, as reported in Fazli et al. (2012), Kauhanen et al. (2006), Khan et al. (2014), Koo et al. (2015), Leeb et al. (2011), Lin et al. (2016), Ma et al. (2014), Punsawad et al. (2010), Soekadar et al. (2015), and Wang et al. (2014).

The variety of brain signals has different signal characteristics (shown in Table 27.1) and can be used therefore for distinct functions. For instance, brain signals can be categorized according to the manner of deployment as being invasive or noninvasive. On one hand, invasive methods are implemented by placing electrodes on the surface of the cortex (i.e., ECoG) and thus provide good signal quality with high temporal and spatial resolution. However, they require surgery for deployment and

<table>
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<tr>
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<th>EEG</th>
<th>MEG</th>
<th>fMRI</th>
<th>NIRIS</th>
<th>ECoG</th>
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<tr>
<td><strong>Deployment</strong></td>
<td>Noninvasive</td>
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<td>Invasive</td>
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<tr>
<td><strong>Temporal resolution</strong></td>
<td>Good</td>
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<td>Low</td>
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<td><strong>Spatial resolution</strong></td>
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<td><strong>Cost</strong></td>
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<td><strong>Portability</strong></td>
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**Note:** EEG, electroencephalography; MEG, magnetoencephalography; fMRI, functional magnetic resonance imaging; NIRIS, near-infrared spectroscopy; ECoG, electrocorticography.
extreme care for stability and against possible infections. On the other hand, noninvasive methods measure the activity from the scalp and hence do not carry the same risks as invasive methods. Thus, they are used more frequently in human research.

Among noninvasive methods, EEG and NIRS are portable, easily deployable, and relatively inexpensive devices. Their wireless implementations are also feasible, making them even more convenient to use. In this respect, MEG and fMRI are immobile machines and require good shielding from the environment, so they are bound to controlled laboratory environments. The EEG and MEG measurements have high temporal resolution, whereas fMRI and NIRS measure the blood oxygenation in the brain, which is a much slower correlate of the brain activity (i.e., lower temporal resolution). Noninvasive methods provide lower spatial resolution in comparison to invasive ones. Among noninvasive methods, fMRI has relatively higher spatial resolution, as it can sample the activity of deep brain structures. In the following, we present several EEG-and-EMG–based BCIs and EEG-and-EOG–based BCIs.

27.4.1 EEG-and-EMG–Based BCIs

Practical BCIs for disabled persons should allow the best available remaining functionalities to be exploited. Sometimes, these users have residual activity of their muscles, and therefore, EEG and EMG signals can be combined in a BCI system. Such a combination allows for very reliable control and smooth handover, even though subjects may become fatigued or exhausted during the day (Leeb et al. 2011; Lin et al. 2016).

Leeb et al. proposed a hybrid BCI combining EEG and EMG (Leeb et al. 2011). Twelve healthy subjects participated in a synchronous experiment, which included four runs composed of 30 trials each. In each trial, the subject was instructed to perform repetitive movements with the left or right hand (i.e., clutching the hand in a fist) for a period of 5 s depending on a visual cue (an arrow pointing to the left or right).

The EEG and EMG signals were separately processed and classified and then fused. The EEG signals were recorded over the motor cortex using 16 electrodes. Using a Laplacian filter, the power spectral density of the EEG was estimated in the band of 4–48 Hz. A canonical variate analysis was used to select the subject-specific features that maximized the separability between the different tasks, and the stable features determined according to cross-validation with the training data were used to train a Gaussian classifier. EMG signals were recorded from four channels over the flexor and extensor muscles of the right and left forearms. The prehensile EMG signals were rectified and averaged (0.3 s) to extract the envelopes. The resulting features thresholded in a subject-specific manner, normalized, and classified based on the maximum distance. Finally, the two classifier probabilities were fused using a native Bayesian approach to generate one control signal (see the details in Leeb et al. 2011).

The accuracy was 73% for EEG activity alone and 87% for EMG activity alone. However, the accuracy was improved to 91% in the hybrid BCI. Furthermore, to simulate fatigue of exhausted muscles, the amplitudes of the EMG channels were degraded over the run time (attenuation from 10% up to 100%), such that the EEG activity became increasingly more important in the fusion data as the EMG muscles became more fatigued. The results showed that increased muscle fatigue led to a moderate and graceful degradation of performance. The subjects could achieve good control of their hybrid BCI independent of their level of muscle fatigue. This represents a distinct advantage of EEG-and-EMG–based BCI systems.

27.4.2 EEG-and-EOG–Based BCIs

Because many disabled persons retain control of their eye movements, for many users, EOG signals are an appropriate option as an input signal for BCI systems. Recently, several studies have combined EEG and EOG to construct hybrid BCIs (Ma et al. 2014; Punsawad et al. 2010; Soekadar et al. 2015; Wang et al. 2014).
In Ma et al. (2014), EOG and EEG signals were combined to control a multifunctional robot. The GUI of the ERP paradigm used in Ma et al. (2014) included eight arrow icons placed in eight directions on the screen (N, W, S, E, NW, NE, SW, SE), where each icon represented one ERP command. For one trial, stimuli (invert facial images) were displayed upon each arrow icon once in a random order. Each stimulus was presented for 100 ms with a 100-ms ISI. When the user focuses on one target icon, the stimulus that flashed on that icon evokes ERPs, including P300 potentials, vertex positive potentials (VPPs), and N170 potentials. In the EOG paradigm, the EOG signals, including vertical EOGs and horizontal EOGs, were used to detect four types of eye movements: blink, frown, wink, and gaze. More specifically, the system detected double blinks, triple blinks, and frowns based on the vertical EOG and detected winks (left/right) and gazes (toward left/right) based on the horizontal EOG.

This hybrid BCI functioned in two modes, an EOG mode and an EEG mode. The two subsystems had separate functions: the EOG-based subsystem was employed for fast-response tasks, and the EEG (ERP)-based subsystem was used for menu-selection tasks. In EOG mode, the system was asynchronous, which indicates that the system continually detects eye movements and that users can send commands using EOG at any time. In EEG mode, the system was synchronous, indicating that there must be an external command to enable/disable the system and that the subject must follow the system’s predefined pace. Here, a frown detected via the eye movement paradigm was used to switch between the EOG and EEG modes.

The EOG and EEG signals were processed separately. For EOG processing, a simple multi-threshold algorithm was proposed for all four types of eye movements, and the details are presented in Ma et al. (2014). The speed, amplitude, and duration of EOGs were used as features to determine an eye movement event. The threshold values were determined by a calibration process before each experiment. For EEG processing, a 700-ms data segment was extracted from the beginning of each flash stimulus and baseline-corrected based on a 100-ms prestimulus interval. A total of 320 such data segments consisting of 40 targets and 280 nontargets were obtained for each subject. Each segment was down-sampled to obtain a data vector with a length of 15. The training samples (i.e., feature vectors) were then formed by the concatenation of 15 temporal points of data segments from eight channels. The extracted feature vectors were used to train an LDA classifier for subsequent online classification.

Two online experiments that included 13 subjects were carried out to verify the proposed system. One experiment was conducted to control a multifunctional humanoid robot, and the other was conducted to control multiple mobile robots. EOG commands were used to control the robots’ movements, and ERP commands were used to activate the robots’ preprogrammed behaviors or to select the control target for multiple robots. The first experiment stimulated a scenario in which the user controlled a humanoid robot to engage in simple communication with other people. The second experiment simulated a scenario in which the user controlled multiple robots to move around and gather information. In each experiment, most of the subjects achieved satisfactory performance, and a few subjects were even able to complete tasks with performances that were comparable to hand operations. The experimental results suggested that there is a complementary effect between eye movements and ERP paradigms and also suggested that this hybrid interface is promising for various BCI applications. Combining eye movements and ERPs can potentially make full use of the advantages of both systems. Using eye movements, the system can achieve a very high ITR, which compensates for the greatest weakness of ERP interfaces. A GUI incorporating ERPs can allow for many commands to be easily integrated and supported.

In this section, we described several promising hybrid BCIs based on multiple signals, including EEG-and-EMG–based BCIs and EEG-and-EOG–based BCIs, and we highlighted their advantages based on the various signal characteristics. Other types of hybrid BCIs based on multiple signals have also been reported, such as EEG-and-fMRI–based BCIs (Krebs and Hogan 2006; Leeb et al. 2011), EEG-and-fNIRS–based BCIs (Fazli et al. 2012), EEG-and-MEG–based BCIs (Kauhanen et al. 2006), and NIRS-and-fMRI–based BCIs (Cui et al. 2011; Hoge et al. 2005; Mehagnoul-Schipper et al. 2002; Strangman et al. 2002).
27.5 HYBRID BCIs BASED ON MULTIPLE INTELLIGENT TECHNIQUES

In recent years, several BCIs that are combined with other intelligent systems have been developed to achieve shared control. These shared control techniques incorporate the strengths of both the user and the assistive device by allowing each user to control different aspects of the system in situations that require contributions from both the user and the assistive device, that is, shared control. In a shared controller, each task incorporates simultaneous contributions from both the assistive device and the human operator, meaning that the tasks are not controlled in a mutually exclusive manner concerning user and machine command signals. In this section, we introduce these shared control systems and discuss several intelligent wheelchairs that are based on BCIs and autonomous navigation systems, in addition to several rehabilitative systems based on BCIs and intelligent robots.

27.5.1 AN INTELLIGENT WHEELCHAIR BASED ON A BCI AND AN AUTONOMOUS NAVIGATION SYSTEM

To control a wheelchair, multi-objective control commands, including start and stop controls, directional control, and speed control, are needed. The task of producing numerous control signals is challenging for an EEG-based BCI. Although multiple control signals can also be obtained using the aforementioned hybrid BCIs (Long et al. 2012a), producing an accurate control command is time-consuming. Furthermore, the continuous control of a wheelchair based on a BCI may induce a heavy mental burden for the user, especially for disabled patients. One feasible solution is to integrate a BCI with automated navigation techniques and to implement shared control.

In a previous study, Zhang et al. develop an intelligent wheelchair that combines an MI- or P300-based BCI and an autonomous navigation system (Zhang et al. 2016). As shown in Figure 27.8, the wheelchair is equipped with a laser range finder (LRF), two encoders, and an array of three ultrasonic sensors. Specifically, an LRF and two encoders are employed to track the position of the wheelchair in real time. An array of three ultrasonic sensors fixed in the front of the wheelchair is used to prevent collisions when new dynamic obstacles, such as pedestrians or pets, appear near the wheelchair. The users first select one of the candidate destinations using the MI- or P300 potential-based BCI system. According to the determined destination and the current location of

![FIGURE 27.8 An intelligent wheelchair based on a BCI and an autonomous navigation system.](image-url)
the wheelchair, the autonomous navigation system plans a path and then navigates the wheelchair to the destination.

To validate the effectiveness of this intelligent wheelchair, two experiments, an experiment based on MI and an experiment based on P300 potentials, were conducted. The experimental results demonstrated the effectiveness of this system and the several advantages of the system, as follows: (i) The candidate destinations and paths are automatically generated based on the current environment, as detected by two webcams, allowing the system to adapt to changes in the environment. (ii) Once the user selects a destination with the BCI, the wheelchair automatically navigates to the destination, and the user does not need to issue additional mental commands. Thus, the user’s required workload is significantly decreased. (iii) While the wheelchair is in motion, the user can issue a stop command via the BCI.

27.5.2 A Rehabilitative System Based on a BCI and an Intelligent Robot

Hybrid BCIs based on multiple intelligent techniques can also be designed by combining a BCI system and an intelligent robot or a prosthesis. Motor recovery after stroke is known to be influenced by enhanced activity of the ipsilesional primary motor cortex induced by motor training. On one hand, studies have shown that effective movement therapy can be delivered by robots (Krebs and Hogan 2006). When a patient is unable to move, the robot provides guidance and assistance to the patient by performing movements with the stroke-affected limb. On the other hand, MI shares many cognitive aspects of movement without including movement execution and thus provides a substitute for movement execution as a means to activate the primary motor cortex. By reestablishing contiguity between cortical activity related to MI and robotic feedback, BCIs that incorporate robot-assisted movement feedback might strengthen the sensorimotor loop and foster neuroplasticity that could facilitate motor recovery. Using this hybrid approach, several rehabilitative systems have been designed that employ an MI-BCI–controlled robot to provide motor feedback to the patient.

Ang et al. combined an MI-based BCI and a haptic knob (HK) robot for arm rehabilitation of stroke patients (Ang et al. 2014). The system setup comprised an EEG cap, EMG electrodes, an EEG amplifier, and an HK robot. During training with the HK robot, the subjects were comfortably seated and instructed to imagine opening and closing their stroke-impaired hand while voluntary movements were restrained by static resistance from the HK robot. Specifically, instructions and feedback were provided via a computer screen to indicate the progress of the HK robot–assisted physical therapy in the form of a picture manipulation task in which a solid frame represented the current position and a dotted frame represented the target position. The EEG-based BCI was used to detect MI while the HK robot provided movement feedback to the subjects.

Twenty-one chronic hemiplegic stroke patients (Fugl-Meyer Motor Assessment [FMMA] score 10–50) were randomly allocated to BCI-HK, HK, or standard arm therapy (SAT) groups. All groups received 18 sessions of intervention for 6 weeks comprising 3 sessions per week and 90 min per session (see the details in Ang et al. 2014). The experimental results showed that the FMMA scores improved in all groups, although no intergroup differences were found at any time points. Significantly larger motor gains were observed in the BCI-HK group than in the SAT group at weeks 3, 12, and 24, but the motor gains of the HK group did not differ from the SAT group at any time point. In conclusion, BCI-HK is effective, is safe, and may have the potential to enhance the motor recovery of chronic stroke patients when combined with therapist-assisted arm mobilization. Similar benefits were observed in another study that investigated chronic stroke patients who utilized an MI-BCI system that included hand and arm orthoses feedback versus those who received random orthoses feedback not linked to the BCI (Ramos-Murguiadlay et al. 2013), suggesting a possible advantage of the use of robot-assisted BCIs in rehabilitation following stroke.

Other hybrid BCIs for shared control have also been reported. For instance, a previous study (Iturrate et al. 2009) reported shared control of a wheelchair based on multi-stages. At each stage, a 3D environmental map, which presented a set of distributed candidate destinations to the user, was
constructed using an LRF. After the user selected a destination using a P300 potential-based BCI, the wheelchair autonomously moved to the selected destination based on the navigation system. Through a series of destination selections and navigations, the final destination could be reached. In another previous study (Ang et al. 2011), a rehabilitative system in which an MI-based BCI was combined with the Innmotion2 MIT-Manus planar shoulder and elbow robotic arm was proposed for stroke patients. The BCI was used to detect MI while the MIT-Manus robot provided movement feedback to the subjects. In summary, hybrid BCIs combined with other intelligent systems may be more reliable, usable, and powerful than traditional “simple” BCI systems.

27.6 DISCUSSIONS AND CONCLUSION

This chapter reviewed the state-of-the-art hybrid BCI techniques. We first described four classes of hybrid BCIs: hybrid BCIs based on multibrain patterns, multisensory hybrid BCIs, hybrid BCIs based on multiple signals, and hybrid BCIs based on multiple intelligent techniques. However, this categorization is not strict because different classes of hybrid BCIs may overlap. For instance, a multisensory hybrid BCI may elicit two or more brain patterns. Next, we briefly analyzed these four classes of hybrid BCI systems, including discussions of their principles, paradigms, experimental results, advantages, and applications. In the following section, we provide several concluding remarks and future studies.

Considering the four classes of hybrid BCIs and their respective applications, we may summarize two fundamental advantages of hybrid BCIs (Li et al. 2016).

1. Improving target detection performance. Hybrid BCIs have been shown to improve target detection performance, as outlined in the aforementioned sections. The two major strategies that lead to these improvements are as follows: (1) The combination of multiple brain patterns, for example, MI-based ERD/ERS, P300 potentials, and SSVEPs, or multiple signals, such as EEG, EMG, EOG, or NIRS. The fusion of multiple brain patterns or multiple signals can be performed at the feature level (e.g., Horki et al. 2011) or at the output level (e.g., Krebs and Hogan 2006; Leeb et al. 2011; Li et al. 2013); (2) The enhancement of brain patterns through the presentation of multisensory stimuli, such as audio-visual stimuli (Wang et al. 2015).

2. Multidimensional/function control. Herein, the implementation of multidimensional or function control based on hybrid BCIs and several application systems have been presented. Three main methods can be used: (1) combining multiple brain patterns to obtain multiple independent control signals, for example, MI-and-P300–based 2D cursor control (Li et al. 2010) and MI-and-SSVEP–based orthosis control (Pfurtscheller et al. 2010b); (2) employing different signal characteristics to perform distinct functions, for example, EEG-and-EOG–based robot control (Ma et al. 2014); and (3) incorporating BCIs with other intelligent systems to achieve shared control, for example, an intelligent wheelchair based on a BCI and an autonomous navigation system (Zhang et al. 2016).

Here, we consider several challenges for further study, and the details are presented in Li et al. (2016). A hybrid BCI system may involve multibrain patterns, multisensory modalities, multiple signal inputs, or multiple intelligent systems. To ensure the effective coordination of these components in a hybrid BCI system, investigations into the related brain mechanisms are needed. However, there have been few brain mechanism studies for hybrid BCIs until now.

Moreover, noninvasive brain stimulation by means of repetitive transcranial magnetic stimulation (rTMS) or transcranial direct current stimulation (tDCS) has driven important discoveries in the field of human memory functions. In recent studies (Capotosto et al. 2015; Roy et al. 2014;
Sparing and Mottaghy 2008), researchers have combined rTMS/tDCS with EEG or fNIRS to assess issues such as location and timing of brain activity, connectivity and plasticity of neural circuits, and functional relevance of a circumscribed brain area to a given cognitive task. Further studies should extend the use of these hybrid approaches from research tools in neuroscience to the treatment of neurological and psychiatric patients.

Furthermore, future studies should focus on the design and implementation of hybrid BCIs. When designing a hybrid BCI based on multibrain patterns, one challenge is identifying the best combination of brain patterns, which will likely differ considerably across users, to accomplish the desired goals (Pfurtscheller et al. 2010a). In designing a multisensory hybrid BCI, one challenge is ensuring that the desired brain patterns are enhanced by the multisensory stimuli. In the future, we may consider more combinations of multisensory stimuli involving visual, auditory, and tactile modalities. For hybrid BCIs based on multiple signals, one challenge is ensuring that the advantages of the different signals are fully exploited, thereby improving the system performance. Furthermore, one should also consider the real-time hybrid BCIs based on EEG and fMRI because of the following factors: high noise in EEG data (produced by fMRI scanner), slow BOLD responses, high dimension, and low time resolution of fMRI data. One potential application of this type of hybrid BCIs is in brain mechanism studies of BCIs. When designing hybrid BCIs for shared control, the paradigm of man–machine adaptation/learning for optimizing the coupling of the user and the machine and establishing a model that can effectively merge the user’s intention and the machine’s decision must be considered. Future studies should focus on these problems. Until now, most hybrid BCI systems, for example, BCI browsers and BCI wheelchairs, as discussed in this chapter, have been designed based on healthy subjects. These systems need to be extended for use by patients, carefully considering the major differences between healthy subjects and patients.

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REFERENCES


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