36 Past and Future of Multi-Mind Brain–Computer Interfaces

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CONTENTS

Abstract

The great improvements in brain–computer interface (BCI) performance that are brought upon by merging brain activity from multiple users have made this a popular strategy that allows even for human augmentation. These *multi-mind BCIs* have contributed in changing the role of BCIs from assistive technologies for people with disabilities into tools for human enhancement. This chapter reviews the history of multi-mind BCIs that have their root in the hyperscanning technique; the *collaborative* and *competitive* approaches; and the different ways that exist to integrate the brain signals from multiple people and optimally form groups to maximize performance. The main applications of multi-mind BCIs, including control of external devices, entertainment, and decision making, are also surveyed and discussed, in order to help the reader understand what are the most promising avenues and find the gaps that are worthy of future exploration. The chapter also provides a step-by-step tutorial to the design and implementation of a multi-mind BCI, with theoretical guidelines and a sample application.

36.1 INTRODUCTION

Brain–computer interfaces (BCIs) have traditionally been employed to help people with disabilities communicate or control prostheses (Wolpaw et al. 2002; see Chapter 4 ["Brain–Computer Interfaces for Motor Rehabilitation, Assessment of Consciousness, and Communication"] by Guger et al. and Chapter 5 ["Therapeutic Applications of BCI Technologies"] by McFarland in this handbook). Many advances have been done in research in the last few decades that have allowed for the development of more reliable BCIs (see Chapter 6 ["Neuroprosthetics: Past, Present, and Future"] by Dambrot). For example, new hardware has improved the signal-to-noise ratio of brain signals recorded and used to control BCIs, while innovative algorithms and machine learning techniques have boosted classification performance. As a result, innovative applications of BCIs have been proposed, targeting a broader range of users (van Erp et al. 2012).

One of the main focuses of this new line of investigation is the development of new BCIs based on the brain activity recorded from *multiple users* simultaneously. These devices have been introduced as *hyperscanning* systems when used for passive applications, such as monitoring the brain activity (Babiloni and Astolfi 2014), and as *multi-mind* (also called *multi-brain* or *multi-user*) *BCIs* for active control, for example, to improve human performance in target detection (Wang and Jung 2011). Despite the fact that this area of research has just recently appeared, a high number of papers have been published in this field. Multi-mind BCIs have shown the potential of improving the performance of single-user BCIs for people with disabilities (Li and Nam 2016), as well as augmenting human performance (Wang and Jung 2011). While this research field is relatively new, much effort has been put in investigating different modalities of implementing a collective brain (Cecotti and Rivet 2014a; Wang and Jung 2011), so that current and future researchers could focus on innovative applications of these technologies.

The aim of this chapter is to provide the reader with an overview of multi-mind BCIs based on electroencephalography (EEG). We assume that the reader is familiar with BCIs (for a detailed introduction to these systems, please refer to Chapter 1 ["Brain–Computer Interface: An Emerging Interaction Technology"] by Nam et al.). We will consider as multi-mind BCIs all those devices that use *the brain activity of at least two participants* to perform an active task (i.e., the BCI is actively being used to achieve a goal, and not only for monitoring, e.g., to move a prosthetic arm or make a selection on the screen). These include both collaborative and competitive BCIs, as long as the state of the interface depends on the brain signals of multiple people. If the users are trying to reach a common goal, the multi-mind BCI will be categorized as a *collaborative BCI*, regardless of the way in which the information from their brains is fused. If, on the contrary, users are competing against each other or are given individual goals that do not allow collaboration between them, we will consider this to be a *competitive BCI*. Both collaborative and competitive BCIs are *active BCIs*, since the brain activity of the participants has a direct impact on the state of the interface. Passive multi-mind BCIs (or hyperscanning systems, see Chapter 3 ["Passive Brain–Computer Interfaces: A Perspective on Increased Interactivity"] by Krol et al.), traditionally used to monitor the brain activity of multiple users while performing a certain task, will not be covered in this chapter.

Occasionally, the name "collaborative BCIs" has been associated with systems where the output depends on a combination of artificial intelligence and single-user BCIs (Göhring et al. 2013; Katyal et al. 2014) and not on the brain signals of multiple users. Such systems are more commonly described as hybrid BCIs (see Chapter 27 ["Hybrid Brain–Computer Interfaces and Their Applications"] by Pan and Li), a term that can refer either to shared control with an artificial agent—for example, when controlling a wheelchair, sensors will stop it if they detect an obstacle (Philips et al. 2007)—or to situations in which multiple (different) signals from the user are used to control the BCI—for example, physiological signals (e.g., amount of sweat and heart rate), behavioral measures (e.g., key presses), or different types of EEG-evoked responses (Müller-Putz et al. 2011). Nevertheless, this definition does not exclude the possibility of creating multi-mind hybrid BCIs.

The organization of this chapter is as follows. Section 36.2 reviews the origin and development of multi-mind BCIs and describes the techniques that have been used in this field, introducing the main technological challenges and open issues. Section 36.3 presents an overview of the main applications of multi-mind BCIs found in the literature. Section 36.4 provides a tutorial on how to build a multi-brain BCI. Finally, in Section 36.5, we outline some suggestions for future developments of BCIs based on brain signals of multiple users.

36.2 THEORETICAL ASPECTS OF MULTI-MIND BCIs

This section reviews different aspects of multi-mind BCIs from a theoretical point of view. We will start by providing a short summary of the origin and evolution of these systems over the last few decades and then consider different features that reflect the state of the art in multi-mind BCIs.

36.2.1 History of Multi-Mind BCIs

The origin of multi-mind BCIs can be found in *hyperscanning*, a technique to measure and analyze the brain activity of two or more people while they participate in a common activity, for example, playing cards (Astolfi et al. 2010). The first EEG hyperscanning results date from 1965 (Babiloni and Astolfi 2014; Duane and Behrendt 1965). Hyperscanning allowed researchers to discover that collaborative and competitive tasks have different effects on the connections in the brains of participants performing behavioral experiments. For a review on hyperscanning, we refer the reader to Babiloni and Astolfi (2014).

The hyperscanning technique was primarily conceived as a way of measuring, at a neurological level, the effects of social interaction. The idea of monitoring multiple people was later used in what can be considered as *passive multi-mind BCIs*. Examples of this can be found in the work of Hasson et al. (2004) and Hasson et al. (2008), in which the authors assessed the effects of feature films on brain activity during free movie watching. The main result of their work was to show that aspects such as movie content, editing, and directing style have a direct impact on the level of control over the viewer's brain activity. Later studies used passive multi-mind BCIs to show the high level of intersubject correlation during natural vision (Bridwell et al. 2015). This discovery made it possible to study the brain's naive responses to stimuli by averaging signals across multiple users, hence increasing the low signal-to-noise ratio that is typical in EEG-based BCIs. Moreover, the high time resolution provided by EEG systems allows researchers to use this technique also for *active multi-mind BCIs*, for example, in those based on event-related potentials (ERPs), which traditionally rely on multiple repetitions of a stimulus in single-user interfaces (Farwell and Donchin 1988; Jiang et al. 2015; Kapeller et al. 2014; Korczowski et al. 2015; Matran-Fernandez and Poli 2015; Vidal 1973).

Multi-mind BCIs started being developed in the 2000s using mainly a competitive form. Ilstedt Hjelm and Browall (2000) conceived a multi-mind BCI as a neurofeedback tool to help people learn how to relax through gamification. Babiloni et al. (2007) also employed the competitive approach in a game with the aim of shortening user training times in modulating alpha and mu rhythms. They were also the first ones to include disabled participants in their study, showing that multi-mind BCIs can also be useful to the disabled community (e.g., for user training). During the following years, the focus was placed mostly on collaborative BCIs, especially for augmenting human capabilities. As we will show below, research in the 2010s was devoted to studying different ways of merging evidence from multiple people (Cecotti and Rivet 2014a,b; De Vico Fallani et al. 2010), identifying an optimal group size (Cecotti and Rivet 2014a; Eckstein et al. 2012; Poli et al. 2014), and, as in the case of single-user BCIs, reducing the number of electrodes while maintaining good levels

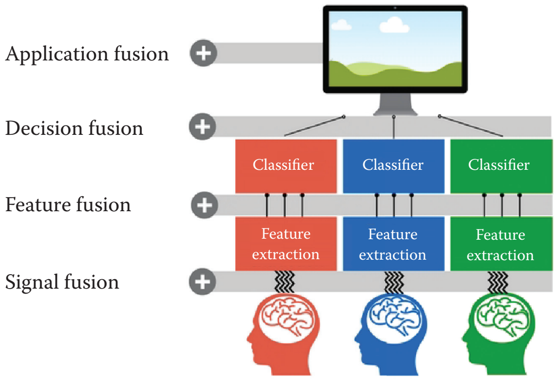

FIGURE 36.1 Different strategies to merge the brain activity in multi-mind BCIs.

of performance (Cecotti and Rivet 2014a). Hence, most of the recent research followed an *offline** approach, in which no interaction from the users was considered.

36.2.2 Implementing a Collective Brain

A traditional single-user BCI is usually composed by a *signal acquisition* module, a *feature extraction* module, and a *decision* module. The brain activity of multiple users can thus be combined at four different levels: *signal*, *feature*, *decision*, and *application* levels (see Figure 36.1).

The simplest mode of combining evidence from multiple users is at the *signal level*. At this level, EEG signals of different users are averaged and either fed into a unique classifier directly, without extracting any feature (Cecotti and Rivet 2014a,b; Jiang et al. 2015; Kapeller et al. 2014; Korczowski et al. 2015; Matran-Fernandez and Poli 2014; Matran-Fernandez et al. 2013; Poli et al. 2013a), or used to perform multi-user analyses, taking advantage of the increased signal-to-noise ratio that can be achieved by averaging trials from multiple users (De Vico Fallani et al. 2010; Matran-Fernandez and Poli 2015).

In a second scenario, features extracted from each user's EEG signals could be merged. The fusion can be done by simple concatenation to form a unique feature vector or any other combination (Eckstein et al. 2012; Wang and Jung 2011), so that only one classifier is used.

Third, the outputs of individually tailored classifiers can be merged. At this level, we should mention the work from Cecotti and Rivet (2014a,b), who studied different modes of combining the BCI decisions on a P300-based collaborative BCI and a steady-state visual evoked potential (SSVEP) multi-mind BCI. Their strategies for merging the classifiers' outputs included majority voting, average of classifiers' outputs, and maximum and minimum values. They found that averaging the classifiers' outputs provided the best performance.

Bonnet et al. (2013) also proposed an additional level of integration of brain signals called the application level. In this case, the implementation of the multi-mind BCI is not done by the BCI itself but by the application operated by the BCI. This is very common in competitive scenarios, where the outputs of different single-user BCIs may be (a) used to control different avatars in a game (e.g., Li et al. 2013), (b) compared to control a unique aspect of the interface according to the intentions of the "winner" (e.g., Ling and Vučković 2016), or (c) taken into account independently for shared control of a unique interface (Bonnet et al. 2013; Le Groux et al. 2010; Li and Nam 2016;

* When talking about offline/online BCIs, we follow the traditional definition: online (multi-brain) BCIs are those in which the brain signals of the users are being processed at the time of collection to control the BCI. On the contrary, an offline BCI is that in which the brain activity of the users is recorded for posterior analysis, and the state of the interface is either static or manipulated by the experimenters.

Schultze-Kraft et al. 2013). Other possible ways of making a final decision in a multi-mind system at the application level include choosing the fastest available output (e.g., if speed is a requirement of the system and it can be safely assumed that faster responders are also more accurate, perhaps in the form of a collaborative hybrid BCI), the most consistent brain activity, or the strongest one (Nijholt and Poel 2016).

A considerable amount of work has been conducted to establish which level of fusion is optimal, obtaining quite consistent results across laboratories and applications. In particular, the two approaches that are often compared are the single-trial averages across participants (i.e., signal level) and fusion at the decision level (usually averaging classifiers' outputs to send a command). Since most of this work has been done based on different ERPs, given the intersubject differences in latencies and amplitudes, it is not surprising that the best performance is obtained when information is merged at the decision level (Cecotti and Rivet 2014a,b; Matran-Fernandez and Poli 2014; Wang and Jung 2011). Such differences in performance are statistically significant (Matran-Fernandez and Poli 2014, 2017), even at the lowest level of fusion.

36.2.3 How Many Minds Are Needed?

Years of research in decision making have shown that bigger groups tend to lead to better decisions (Kerr and Tindale 2004). The aggregation of information from different sources can help reduce bias and increase certainty in the system's final output. In general, this is also true in the field of collaborative BCIs, where increasing group sizes has steadily led to better classification performance (Cecotti and Rivet 2014a,b; Matran-Fernandez and Poli 2017; Wang and Jung 2011) and group decisions (Eckstein et al. 2012; Poli et al. 2014; Valeriani et al. 2016). However, this increase in performance does not follow a linear relationship with the number of people included in the BCI. Indeed, there is a tipping point at group sizes between 5 and 10 users (Eckstein et al. 2012), above which the addition of a new member to a group might not be cost-effective (i.e., the small increase in performance brought upon by this member does not justify the expenses required for the additional hardware). This tipping point will vary depending on the complete system and should be studied depending on the specific application at hand. For example, Eckstein et al. (2012) found that seven brains were required to match the mean behavioral accuracy of a single observer (not using a BCI) when making perceptual decisions.

As we will show in Section 36.2.4, it might be possible to reduce the number of users of a collaborative BCI by finding users who perform similarly. Hence, in some applications, it may be worth developing a study of potential candidates and select them to perform the task at hand to obtain a small group of users that are able to outperform a bigger one at a fraction of the total cost.

36.2.4 Influence of Participant Similarity When Forming Groups

Depending on the level of information fusion, taking into account how similar the brain's responses from multiple users are may boost performance when creating collaborative BCIs, regardless of the metric used to assess it. This was first mentioned by Matran-Fernandez et al. (2013) in a target detection task following a rapid serial visual protocol. The authors noticed that the increase in performance obtained by pairs of observers was higher when the classification accuracy of their individual BCIs was similar, irrespective of the actual individual accuracy values. Korczowski et al. (2015) also noticed a high correlation between user similarity and BCI performance but did not explore further.

Perhaps the most comprehensive study of this effect to date is that of Matran-Fernandez and Poli (2017), who showed numerically that the biggest gains for groups of sizes between 2 and 11 can be obtained when participants are very similar, both at the signal and the classifier fusion levels, and that these gains are statistically significant even when compared against the best individual of the group. The higher gains achieved when merging the brain signals at the decision level (with respect to the signal level) could be due to the fact that the groups were created based on classification performance, which might give an inherent advantage to this fusion strategy. When fusion is done at the signal level, the differences in peak latencies and amplitudes between different users could be employed to form the groups based on similarity of their ERPs, which might yield better BCI performance (Matran-Fernandez and Poli 2016).

It should be noted that the results described above are referred to collaborative BCIs. To the best of our knowledge, there is no study of participant similarity/dissimilarity and its effects in competitive BCIs. Competitive BCIs could highly benefit from grouping participants according to their level of control, especially when used to reduce training times—for example, when learning to control the mu and alpha rhythms (Babiloni et al. 2007)—which may increase the motivation of the users.

36.2.5 Challenges

There are some challenges that apply to BCIs, regardless of the number of users needed to control it. For example, in cue-based BCIs, there is the need of synchronizing the whole system, from the display to the acquisition modules and, possibly, also to the processing and feedback parts of the BCI. This problem is accentuated in multi-mind BCIs, both self-paced and cue-based, as the synchronization needs to be done to multiple displays (if applicable), acquisition devices, and processing nodes (Cecotti and Rivet 2014b). This issue is particularly important in online systems, where a small jitter might have a large impact in performance of both collaborative (e.g., if merging information at the signal level) and competitive (e.g., where the difference in timing may result in an advantage for one of the users) systems.

Moreover, online systems are less flexible than offline ones for posterior data analysis, especially those that involve some sort of interaction between the users. If the communication between the participants modifies in some way their behavior, regrouping users (a technique widely used in offline collaborative BCIs) might be a hard task. However, offline studies do not allow investigating the impact of such interaction, which might play a crucial role in the final online BCI. Unfortunately, this aspect remains unexplored in multi-mind BCIs of the collaborative type.

Online multi-mind BCIs also require multiple acquisition devices, which increases the overall cost of the system, as opposed to the single piece of EEG equipment that is necessary for running offline experiments. Despite the recent appearance of low-cost EEG systems, which aim at reducing preparation times, using a multi-mind BCI remains quite costly, in terms of both time and money.

There are also difficulties associated with the different levels of merging information in the multi-mind system. Leaving aside those of precisely synchronizing all the devices that are part of the multi-mind BCI, the signals from multiple users will vary in amplitude and latency due to electrode positioning and functional anatomy. Thus, it is necessary to normalize the EEG signals from each participant, especially when fusion occurs at the signal level. The same applies to other levels of fusion, where either features or classifier's outputs should be on the same scale to guarantee that the differences between them do not affect performance.

Another challenge that arises in multi-mind BCIs is that of finding a metric that can be used to compare such systems with single-user BCIs. Measures such as accuracy or the area under the receiving operating characteristic are still valid. However, if time should be considered (as it is done, e.g., by including the number of repetitions needed to control a speller in the information transfer rate [ITR], a standard of BCI performance), the formula for the ITR needs to be modified accordingly to allow for the number of users (Cecotti and Rivet 2014a).

36.3 APPLICATIONS

The first BCI using data recorded from multiple brains to augment performance dates back to 2011, when Wang and Jung (2011) proposed a collaborative framework for BCIs in which data from multiple participants performing a movement planning task were fused together. Since then, multi-mind BCIs have been applied to a variety of contexts, which are reviewed in this section.

36.3.1 Communication

The first single-user BCIs—the matrix spellers—were developed to help people with severe disabilities communicate (Farwell and Donchin 1988). Despite recent advances (Townsend and Platsko 2016), the single-trial performance of such systems (typically based on the P300 ERP) is still far from perfect (see Chapter 18 ["Gentle Introduction to Signal Processing and Classification for Single-Trial EEG Analysis"] by Blankertz). Although averaging brain signals across a number of repetitions of the same stimulus leads to higher accuracy, this approach also reduces speed as it requires to record the ERPs associated to the same stimulus multiple times. However, BCI spellers might represent the only opportunity for locked-in patients to communicate, so every little step to improve reliability and practicality of these systems could represent a great benefit to their users.

P300-based BCIs are an attractive test bed for multi-mind BCIs, since they rely on the presence or absence of a relatively large EEG component. Since the original speller from Farwell and Donchin (1988) relied on this ERP, several researchers have tested the performance of multi-mind BCIs on spellers, admitting that it is not a realistic application of such devices, due to the need for the multiple users to agree on what to spell beforehand (Cecotti and Rivet 2014a; Kapeller et al. 2014).

Cecotti and Rivet (2014a) showed in an offline analysis how a cooperative BCI could be used to improve the accuracy of the P300 speller using different methods (summarized in Section 36.2.4). Their results suggested that averaging the BCI outputs seemed to be the best method for implementing a cooperative BCI. Increasing the group size led to better performance, as would have been the case if the number of repetitions of each row/column of the speller had been increased in a single-user BCI, although they showed that single-trial multi-mind BCIs perform better than multi-trial single-mind BCIs. However, that study did not investigate a combined approach where collaborative BCIs are based on the aggregation of trials over time and over participants.

The performance of a collaborative P300-based BCI speller was validated online by Kapeller et al. (2014), who showed that the aggregation of EEG signals of eight participants could allow a single-trial BCI to reach perfect performance. However, it was not stated what the performance would have been with fewer participants, and it raises the question of whether perfect accuracy is really needed or if it is possible to sacrifice some of the performance for a lower number of users.

Although the two studies presented in this section recognized that communication is not a practical application for collaborative BCI, their results helped show the potential of multi-mind BCIs, opening the way to more practical applications.

36.3.2 Control of External Devices

Another traditional application of BCIs is to control external devices (Wolpaw et al. 2002). Current single-user BCI systems can achieve reasonable performance for *simple control* tasks, such as controlling a cursor (Citi et al. 2008; Wolpaw et al. 1991) or using a robotic arm to reach and grasp an object (Hochberg et al. 2012), but they might not be accurate enough to control *complex devices*, such as manipulators with many degrees of freedom. In order to enhance accuracy of such complex devices, researchers have developed hybrid BCIs that take into account domain knowledge from the area to automatize certain tasks (Müller-Putz et al. 2011; Philips et al. 2007).

Multi-mind BCIs have also been introduced in this area to guarantee reliable control of external devices based only on neural signals. Three main approaches have been explored in this area: (a) single BCI users take turns to operate a shared external device, (b) a collaborative BCI is used to control the whole device, or (c) multiple single-user BCIs control different parts of a shared device (e.g., roll, pitch and yaw in a plane). The strategy of taking turns does not seem to be very promising as groups of users either perform on par (Li and Nam 2016) or worse (Nam et al. 2013) than single BCI users. Therefore, this section will mainly focus on strategies (b) and (c).

Collaborative BCIs were first applied to simple control tasks, such as a movement-planning task (Wang and Jung 2011) where participants were told the type of movement to perform (saccade to target, reach without eye movements, or reach with eye movements) and the direction (left, right, or center). Merging information from 20 participants at the signal, feature, and classifier levels yielded accuracies of up to 95% (accuracy in the single-user case was 66%) when predicting the direction of the movement (left vs. right) up to 250 ms before the actual motor response.

Poli et al. (2013a) developed a collaborative online ERP-based BCI where the neural signals from two users were used jointly to control a spacecraft simulator through an analog BCI. They used the normalized path length and the absolute angle deviation to compare the performance of their multi-mind BCI with that of single-user BCIs, showing that the former was significantly better than the latter. This suggests that collaborative BCIs could provide a better control of the simulator than single-user BCIs. Moreover, they showed that the success rate of single-user BCIs was much higher (67.5%) than that of a random controller (6.2%).

Other researchers developed SSVEP-based collaborative BCIs that allowed pairs of participants to operate a robot by sending target sequences of commands (Li and Nam 2016). The EEG signals of the two participants were processed by two independent BCIs and then aggregated following a majority rule. The robot knew the sequence of tasks and reacted only to correct commands, so no error correction was needed in case of BCI misclassification. An interesting aspect of those studies was the fact that they included a cohort of patients with amyotrophic lateral sclerosis, who were also able to operate the system with better accuracy and in less time than single BCI users.

The studies presented in this section showed that multi-mind BCIs can be used to control a broad range of external devices. We envision that other innovative applications will be proposed in the following years. For example, multi-mind BCIs could be used to jointly control an exoskeleton by a physiotherapist and a patient, to enhance the training of the latter. Still within the scope of rehabilitation, competitive multi-mind BCIs can also be used to improve the level of engagement of the patient while reducing training times (Ling and Vučković 2016). Finally, multi-mind BCIs could also be used as a switch to decide which agent should have the control (e.g., in an aircraft operated by an automated system and two pilots, the BCI could be used to temporarily override the artificial intelligence in case of perceived hazards).

36.3.3 Video Games

Games provide a nice framework for testing the performance of a BCI while keeping users motivated and entertained. Gaming was one of the first nonmedical applications of BCIs (see Chapter 11 ["BCI and Games: Playful, Experience-Oriented Learning by Vivid Feedback?"] by Kober et al.), showing a growing interest by both researchers and the entertainment industry (Bos et al. 2010; Marshall et al. 2013; Nijholt et al. 2009; van Erp et al. 2012). Of course, there are many varieties of games, each with different interaction modalities. Some games only allow a low number of commands (e.g., arcade games), making BCI control feasible (Marshall et al. 2013). More complex games (e.g., simulation or role-playing games) might require users to quickly react to different events, or provide them with a myriad of possible actions. In the latter case, BCIs could be used as an additional alternative input, for example, to change the shape of the avatar in World of Warcraft (van de Laar et al. 2013).

The high number of actions supported by the majority of video games suggest that a promising way of using multi-mind BCIs in this area could be by sharing the control (see Section 36.2.2). This was one of the approaches tested by Schultze-Kraft et al. (2013), where pairs of participants navigated through a 2-D maze by controlling one dimension each.

Multi-mind BCIs have also been used in sports video games. Bonnet et al.'s (2013) BrainArena involved pairs of users that scored goals on the left or right side of the screen using two motor imagery BCIs. The outputs of the individual classifiers were aggregated to produce the command to be sent to the game. They tested a cooperative and a competitive manner. The performance achieved by the paired users in the cooperative mode was compared with that obtained by (a) paired users in the competitive mode and (b) single BCI users. Although no significant differences in performance between the three methods were found, comparisons in the three forms using only the best participant of each pair showed that his or her performance was significantly better in collaborative mode with respect to single-user mode.

The application fusion mode used in the competitive approach investigated by Bonnet et al. (2013) compared the outputs of the individual classifiers to decide which user's command to use to control the ball (a unique avatar). An alternative approach in competitive multi-mind BCIs would be to have users controlling different avatars in the game through independent BCIs, for example, to control multiple cars in a racing game (Li et al. 2013) or play BrainPong (Babiloni et al. 2007) and BrainBall (Ilstedt Hjelm and Browall 2000). This is also the approach that was used in the BCI race of Cybathlon 2016 (see www.cybathlon.com), where paralyzed participants used a self-paced BCI to overcome different virtual obstacles.

Multi-mind BCIs have also been employed to develop innovative video games where users score points based on their ability to modulate their brain activity. In this direction, Ling and Vučković (2016) developed a cooperative and a competitive video game. In the former, users had to modulate their alpha band powers to be as similar as possible to score a point, while in the latter, the user with the highest power would win.

Another category of video games where multi-mind BCIs have been applied is arcade games. Korczowski et al. (2015) developed a two-user BCI video game based on Space Invaders in which users scored extra points if they were able to reduce the number of repetitions needed for successful selection of a target. They fused information at the classifier level, using a novel method based on the assumption that the EEG signals recorded from users performing the same trials are *not* independent. While this is a reasonable assumption when users share a common goal and are presented the same stimuli, it would not be valid for competitive scenarios. However, this application shows how multi-mind BCIs could make classic games even more exciting.

Multi-mind BCIs increase the range of possible applications of BCIs in the game industry. Various types of multi-mind BCIs have been proposed in the last few years, adopting different approaches to competitive and collaborative gaming. For a review, the reader could refer to Nijholt and Poel (2016) and Nijholt (2015). Even though playing a video game using only a BCI is still difficult due to the high effort needed to control the BCI, which, could also affect the social interaction between users (Obbink et al. 2012), multi-mind BCIs could be used with very simple games to increase engagement of users while learning to modulate their brainwaves. However, shared-control multi-mind BCIs could already be used as a complementary input for complex video games. We envisage that future applications of multi-mind BCIs in games will be in these two contexts.

36.3.4 Target Detection and Decision Making

Decision making is one of the most promising applications of multi-mind BCIs. Every day, we have to make decisions in various situations, some of which are critical and making the wrong choice could result in dramatic consequences. Research in decision making has established that groups generally make better decisions than individuals due to group's abilities to integrate multiple percepts and information (Kerr and Tindale 2004). On the basis of these findings, BCI researchers have started investigating the possibility of using collaborative BCIs to keep the advantages of groups in decision accuracy and the intrinsic ability of the BCI to bypass the motor channels and accelerate decision making.

Considering the broad range of applications of decision making and the influence of psychology experiments on BCI research, researchers have mostly applied multi-mind BCI to target detection tasks, where groups of users have to decide whether a target object/person is present or not in a scene. A first attempt in this direction was made by Wang et al. (2011), who integrated EEG signals from multiple participants performing a detection task. Users were asked to release a button when they saw a target stimulus. The detection accuracy achieved by the collaborative BCI was significantly superior to that obtained with single-user BCIs. Furthermore, as in the case of Wang and Jung (2011), the multi-mind BCI was able to accelerate the decision with respect to the motor action. A following study (Yuan et al. 2013) validated these results with an online BCI with groups of six participants, showing that the multi-mind BCI was more accurate than the actual key releases.

These studies demonstrated the potential of collaborative BCIs to improve and accelerate target detection. However, the results were obtained with very simple tasks. In recent years, multi-mind BCIs have been applied to progressively more complex and challenging decision-making tasks, including face recognition (Jiang et al. 2015), detection of visual targets in slow (Yuan et al. 2012) and rapid presentation of images (Matran-Fernandez et al. 2013; Stoica et al. 2013), and target localization within images (Matran-Fernandez and Poli 2014, 2017). Studies from Matran-Fernandez and collaborators also found that pairing participants on the basis of their similarity in performance could further enhance the accuracy of the multi-mind BCI.

The studies mentioned so far used multi-mind BCIs to improve the performance of single-user BCIs. However, in order to present BCIs as an alternative way to make decisions, their performance should be compared with that obtained using behavioral decisions. In a study on decoding the neural patterns of collective wisdom (discriminating between pictures of cars and faces), Eckstein et al. (2012) compared the performance obtained by a multi-mind BCI with that achieved by non-BCI observers. While the multi-mind BCI was faster than the behavioral decision, it required at least seven users to achieve the same accuracy of individual observers. With such results, the authors stated that it was hard to envision scenarios for which the neural voting would replace standard behavioral voting practices.

In order to overcome the limitations of the multi-mind BCI shown by Eckstein et al. (2012), Poli et al. (2013b) proposed a *hybrid* collaborative BCI that recorded the behavioral responses from multiple participants and used the neural signals to estimate the probability of each individual decision to be correct and provide a measure of "confidence" for each user. The confidence was then used to weigh individual responses and obtain group decisions. This approach was tested with a visual pattern matching task (Poli et al. 2014). The authors showed that, for most group sizes (up to 10 users), the decisions made using the hybrid collaborative BCI were superior to those made by the best individual and those made by equally sized non-BCI groups using the standard majority. Similar results were obtained in visual search tasks using geometrical shapes (Valeriani et al. 2016) and realistic stimuli (Valeriani et al. 2015, 2017b) and for face recognition (Valeriani et al. 2017a).

Applications of multi-mind BCIs to decision making are among the most promising avenues for this technology. Hybrid collaborative BCIs could be used to assist groups, especially in critical scenarios where erroneous decisions could cause loss of lives or money. Focus should be placed on validating these approaches with online experiments, using more realistic decision-making tasks to accelerate the deployment of these technologies.

36.3.5 Music

Repairing or augmenting human cognitive or sensorimotor functions is one of the major applications of BCIs. However, biomedical engineers and neuroscientists have occasionally joined forces with artists to use BCIs as an alternative way to produce and perform music (Miranda and Castet 2014; see Chapter 10 ["BCI for Music Making: Then, Now, and Next"] by Williams and Miranda) and other arts (Zioga et al. 2014; see Chapter 9 ["Toward Practical BCI Solutions for Entertainment and Art Performance"] by Pradhapan et al.).

In music, single-user BCIs have been used to produce melodies from the EEG. However, music could also be made by several people, for example, in an orchestra where every member plays a different instrument, hence adjusting to our definition of multi-mind BCIs. This idea was proposed by Le Groux et al. (2010). Their "multimodal brain orchestra" was composed of four members, two of them controlling an SSVEP-based BCI that modulated the articulation and accentuation of pre-composed sounds, and the other two equipped with a P300-based BCI that allowed the addition of discrete sound events, plus a director with a Wii Remote whose accelerometer controlled the tempo and decided which sound should be played. This framework showed how paradigms developed for common BCI applications (e.g., the P300 speller) could also be used in other contexts.

Music can also be used to evoke emotions. This is what Eaton et al. (2015) envisioned: valence and arousal can be derived from EEG data, so they proposed a music generator that would generate a piece based on the current states of two users in order to drive them to a common state. However, to the best of our knowledge, this idea was not brought to life.

In other arts, multi-mind BCIs have been used to support and guide the creation of polygons through interactive genetic algorithms (Kattan et al. 2015), an application that could easily lead to the production of abstract paintings.

36.4 TUTORIAL

The previous sections provided an introduction to the theory behind multi-mind BCIs and the main applications that have been explored for this technology. On the basis of this information, here we summarize the main design choices that a researcher should make when implementing a multi-mind BCI. Some of these are related, as they result from decisions made at an earlier stage. Hence, a bad design choice made at an initial stage could lead to major drawbacks later on. However, it is always possible to revert to a previous design choice and attempt a different path.

To help the reader follow this tuning process, we will use an example scenario in this section: the design of a multi-mind BCI to assist investors in deciding whether or not to buy a stock. At the end of each step of the tutorial, we will describe the design decision we would make in this context.

36.4.1 Application

The first step of designing a system is deciding the problem that it should solve. This decision involves the area of application and will influence most of the following decisions regarding the technical implementation of the system. Most of the applications you may have in mind could be fitted in one of the main categories described in Section 36.3, which might help in deciding which approach to follow. This decision will also determine the type of output the BCI should provide: a continuous output is usually appropriate for control applications, while a discrete one is adopted by most decision-making applications, where the number of possible outcomes is limited.

Example: the application would clearly fall under the decision-making category (see Section 36.3), as the BCI has to support investors to make a decision. Also, the type of output of the BCI would be binary, as the possible decisions available are either to buy or not that stock (to simplify, we assume the investors could only buy one stock, as the problem of deciding which or how many stocks to buy would be different).

36.4.2 Number of Users

Deciding the number of users that will operate the multi-mind BCI is another important step of the design, directly related to the requirements of the system. On the one hand, as we showed in Section 36.2.3, a higher number of users results in better performance. On the other hand, more users also require more resources for data acquisition (e.g., electrodes and amplifiers), processing, and classification, which will in turn increase the *cost* of the multi-mind BCI.

This design choice is also highly dependent on the application of the multi-mind BCI. For most purposes, a few users are usually sufficient for adequate control and communication applications while keeping the system practical. When it comes to decision making, however, a higher number of users might be needed, especially when considering critical decision making (e.g., in finance, health, or defense). If there is a non-BCI application that the multi-mind is supposed to replace, a good starting point is to choose this number based on the non-BCI number of people needed and adjust the number afterward.

Example: the decision to be made is critical, especially if the amount to invest is large. At the same time, bigger groups will lower individual profits. Hence, our choice is to use a group of between two and four investors to operate the multi-mind BCI.

36.4.3 Real-Time Requirement

A BCI would usually work *offline* or *online*. Offline BCIs are generally used for testing and analysis purposes, allowing the brain signals to be acquired at one time and process them at a different time. On the contrary, online BCIs must satisfy real-time requirements, which may change depending on the application: a few seconds can be acceptable in some areas, while for control of external devices, the BCI response should arrive within milliseconds.

There is a trade-off between the time needed to issue a command and the accuracy of that command. In the case of single-trial decisions, it might be preferable to increase the number of users operating the multi-mind BCI to enhance the accuracy. In this way, the BCI would still benefit from quick outputs without sacrificing speed. As in the case of single-user BCIs, it is a good idea to first test a system offline to determine and adjust the requirements and then transition to online operation. However, this transition may not be straightforward, as it may be necessary to change some processing methods that are too computationally heavy for the resources available.

Example: the fast-changing nature of stock markets implies that our multi-mind BCI needs to be able to produce quick outputs (possibly with a few seconds of margin). Given that most of the approaches found in the literature rely on algorithms that are capable of dealing with single-trial decisions in real time, the system could first be validated through an offline analysis (to help decide the number of users required) but quickly migrate to an online system for it to be relevant.

36.4.4 Operation Mode

This is the core step of the design process, as it requires choosing what type of signals the multi-mind is going to work with, together with the algorithms needed for processing the neural signals and, if necessary, provide relevant feedback to the users. If using evoked potentials, as is the case of target detection systems, a way of displaying the information is needed. Most of the decisions required for the implementation of the BCI, however, are the same required to implement a single-user BCI, so we will not analyze them here, referring the reader to the relevant literature (e.g., Chapter 23 of this handbook). It should also be noted that, in the case of online operation, training data are needed to tune the machine learning component of the BCI.

Example: investors will be shown graphs representing the past story of the stock that they are trying to decide on. They could be given the opportunity to select how far into the past they want the information and also the evolution of prices for other related stocks. In order to train the BCI, investors could be asked to decide whether to buy or not at different points of the timeline (with no information of the future evolution from that point).

36.4.5 Fusion of Brain Signals

As explained in Section 36.2.4, the brain signals from multiple people could be fused at different levels. Even if the literature shows that voting methods outperform signal and feature fusion, different multi-mind BCIs might benefit from different strategies, and it is up to the developer to study which one is the most suitable for his or her purposes. For example, if the aim of the BCI is to exploit the cognition processes of the group, it may be better to average EEG data directly instead.

If the signals are combined at the decision level, a myriad of approaches is still possible (e.g., simple majority, weighted majority, second-layer classifiers, etc.). This choice will have an impact on the complexity of the whole system. An important aspect to consider is how to deal with the special case where a tie is generated, which might be frequent if using simple majority or impossible if using a classifier.

Example: considering the low number of operators chosen and the possibility of having only two of them, in order to avoid ties, we decided to adopt a weighted majority approach to fuse the decisions of the investors. In this case, the weights could be given by their levels of expertise or assigned through machine learning.

36.5 FUTURE DIRECTIONS

Less than a decade ago, the idea of fusing brain signals from multiple people to control a device looked like it was taken from a science fiction movie. Recent advances in neuroscience and BCI research have now made it possible through multi-mind BCIs, which, in turn, have given rise to many interesting applications. However, multi-mind BCIs have still many challenges to face, suggesting that further advances are needed in this field. One of the issues to be investigated is related to the sociological aspects of multi-mind BCIs (Bonnet et al. 2013; Cecotti and Rivet 2014a,b; Nijholt and Poel 2016). Although several groups have compared individual performance when alternating between collaborative and competitive scenarios with a multi-mind BCI (e.g., Bonnet et al. 2013), to date, very little research has been conducted on how team design, collaboration, and motivation can influence task performance in collaborative BCIs (e.g., Schultze-Kraft et al. 2013). Multi-mind BCIs give us the opportunity to study motivation and reward using ERP characteristics, for example, in competitive or collaborative modes (Cecotti and Rivet 2014a). Moreover, the fact that the performance of the system would depend on the group and not on a single individual might have an impact on how success or failure is reflected in the neural signals (Cecotti and Rivet 2014b).

Some of the applications presented in Section 36.3 will likely be explored and studied in the following years, while others may progressively be left out because they are naturally single-user (e.g., communication). We believe that using multi-mind BCIs for decision making is the most promising application, since it is directly applicable to a range of daily problems. The transition from target detection tasks used in current research to more advanced decision-making tasks (e.g., including several possible answers) will not be easy. We believe that the advances in the understanding of the human brain will help researchers identify and better characterize the processes associated with the formation of a decision and develop multi-mind BCIs that are more capable of decoding the intentions of the users. Developing low-cost EEG headsets will also affect the adoption of these systems, especially in video games and other entertainment applications that are naturally multi-user and are interesting for the general public. Furthermore, multi-mind BCIs also have the potential to be used to control devices that are too complex to operate for a single person. This could be in the form of assisting manual operations (e.g., passive systems that monitor attention or active ones for enhancing human performance) or fully operating a device via brain signals.

Multi-mind BCIs could also be used as tools to replicate social situations and give us a better understanding of social psychology (Cecotti and Rivet 2014a), to access collective mental states (Eckstein et al. 2012; cf. Chapter 8 ["Affective Brain–Computer Interfacing and Methods for Affective State Detection"] by Daly), or as a tool for neuro-marketing. In a futuristic world, they could be used in classrooms or theaters to give feedback to teachers or performers about the cognitive state of the listeners (Cecotti and Rivet 2014a). If movies produce high intersubject correlations (Bridwell et al. 2015), is the same true for real-life experiences such as a live performance?

New and established researchers in multi-mind BCIs should not limit their imagination to traditional applications and continue to conceive innovative uses of this technology, hence shaping the future of human enhancement and new interfaces.

REFERENCES

Astolfi, L., J. Toppi, F. De Vico Fallani et al. 2010. Neuroelectrical hyperscanning measures simultaneous brain activity in humans. *Brain Topography* 23 (3): 243–256.

Babiloni, F., and L. Astolfi. 2014. Social neuroscience and hyperscanning techniques: Past, present and future. *Neuroscience & Biobehavioral Reviews* 44 (2014): 76–93.

Babiloni, F., F. Cincotti, M. G. Marciani et al. 2007. The estimation of cortical activity for brain–computer interface: Applications in a domotic context. *Computational Intelligence and Neuroscience* 2007 (91651): 1–7.

Bonnet, L., F. Lotte, and A. Lécuyer. 2013. Two brains, one game: Design and evaluation of a multi-user BCI video game based on motor imagery. *IEEE Transactions on Computational Intelligence and AI in Games* 5 (2): 185–198.

Bos, D. P-O., B. Reuderink, B. van de Laar et al. 2010. Brain–computer interfacing and games. In *Brain–Computer Interfaces*, edited by D. S. Tan and A. Nijholt, 149–178. London: Springer.

Bridwell, D. A., C. Roth, C. N. Gupta, and V. D. Calhoun. 2015. Cortical response similarities predict which audiovisual clips individuals viewed, but are unrelated to clip preference. *PLoS ONE* 10 (6): e0128833.

Cecotti, H., and B. Rivet. 2014a. Subject combination and electrode selection in cooperative brain–computer interface based on event related potentials. *Brain Sciences* 4 (2): 335–355.

Cecotti, H., and B. Rivet. 2014b. Performance estimation of a cooperative brain–computer interface based on the detection of steady-state visual evoked potentials. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2059–2063.

Citi, L., R. Poli, C. Cinel, and F. Sepulveda. 2008. P300-based BCI mouse with genetically-optimized analogue control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 16 (1): 51–61.

De Vico Fallani, F., V. Nicosia, R. Sinatra et al. 2010. Defecting or not defecting: How to "Read" human behavior during cooperative games by EEG measurements. *PLoS ONE* 5 (12): e14187.

Duane, T. D., and T. Behrendt. 1965. Extrasensory electroencephalographic induction between identical twins. *Science*, 150 (3694): 367.

Eaton, J., D. Williams, and E. Miranda. 2015. The space between us. Evaluating a multi-user affective brain–computer music interface. *Brain–Computer Interfaces* 2 (2–3): 103–116.

Eckstein, M. P., K. Das, B. T. Pham, M. F. Peterson, and C. K. Abbey. 2012. Neural decoding of collective wisdom with multi-brain computing. *NeuroImage* 59 (1): 94–108.

Farwell, L. A., and E. Donchin. 1988. Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology* 70 (6): 510–523.

Göhring, D., D. Latotzky, M. Wang, and R. Rojas. 2013. Semi-autonomous car control using brain computer interfaces. In *Proceedings of the 12th International Conference on Intelligent Autonomous Systems (IAS)*, 393–408.

Hasson, U., O. Landesman, B. Knappmeyer, I. Vallines, N. Rubin, and D. J. Heeger. 2008. Neurocinematics: The neuroscience of film. *Projections* 2 (1): 1–26.

Hasson, U., Y. Nir, I. Levy, G. Fuhrmann, and R. Malach. 2004. Intersubject synchronization of cortical activity during natural vision. *Science* 303 (5664): 1634–1640.

Hochberg, L. R., D. Bacher, B. Jarosiewicz et al. 2012. Reach and grasp by people with tetraplegia using a neurally controlled robotic arm. *Nature* 485 (7398): 372–375.

Ilstedt Hjelm, S., and C. Browall. 2000. Brainball—using brain activity for cool competition. In *Proceedings of NordiCHI 2000*, 177–188.

Jiang, L., Y. Wang, B. Cai, Y. Wang, W. Chen, and X. Zheng. 2015. Rapid face recognition based on single-trial event-related potential detection over multiple brains. In *7th Annual International IEEE EMBS Conference on Neural Engineering*, 106–109.

Kapeller, C., R. Ortner, G. Krausz et al. 2014. Toward multi-brain communication: Collaborative spelling with a P300 BCI. In *International Conference on Augmented Cognition*, 47–54.

Kattan, A., F. Doctor, and M. Arif. 2015. Two brains guided interactive evolution. In *2015 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 3203–3208.

Katyal, K. D., M. S. Johannes, S. Kellis et al. 2014. A collaborative BCI approach to autonomous control of a prosthetic limb system. In *IEEE International Conference on Systems, Man and Cybernetics*, 1479–1482.

Kerr, N., and R. Tindale. 2004. Group performance and decision making. *Annual Review of Psychology* 55 (1): 623–655.

Korczowski, L., M. Congedo, and C. Jutten. 2015. Single-trial classification of multi-user P300-based brain–computer interface using Riemannian geometry. In *37th Annual International Conference of IEEE Engineering in Medicine and Biology Society*, 1769–1772.

Le Groux, S., J. Manzolli, and P. F. M. J. Verschure. 2010. Disembodied and collaborative musical interaction in the multimodal brain orchestra. In *Proceedings of the International Conference on New Interfaces for Musical Expression*, 309–314.

Li, J., Y. Liu, Z. Lu, and L. Zhang. 2013. A competitive brain computer interface: Multi-person car racing system. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)*, 2200–2203.

Li, Y., and C. S. Nam. 2016. Collaborative brain–computer interface for people with motor disabilities. *IEEE Computational Intelligence Magazine* 11 (3): 56–66.

Ling, P., and A. Vučković. 2016. Competitive and collaborative multiuser BCI. In *Proceedings of the 6th International Brain–Computer Interface Meeting*, 228.

Marshall, D., D. Coyle, S. Wilson, and M. Callaghan. 2013. Games, gameplay, and BCI: The state of the art. *IEEE Transactions on Computational Intelligence and AI in Games* 5 (2): 82–99.

Matran-Fernandez, A., and R. Poli. 2014. Collaborative brain–computer interfaces for target localisation in rapid serial visual presentation. In *6th Computer Science and Electronic Engineering Conference (CEEC 2014)*, 127–132.

Matran-Fernandez, A., and R. Poli. 2015. Event-related potentials induced by cuts in feature movies and their exploitation for understanding cut efficacy. In *7th International IEEE EMBS Conference on Neural Engineering*, 74–77.

Matran-Fernandez, A., and R. Poli. 2016. Brain–computer interfaces for detection and localisation of targets in aerial images. *IEEE Transactions on Biomedical Engineering* 64 (6): 959–969.

Matran-Fernandez, A., and R. Poli. 2017. Towards the automated localisation of targets in rapid image-sifting by collaborative brain–computer interfaces. *PLoS ONE* 12 (5): e0178498.

Matran-Fernandez, A., R. Poli, and C. Cinel. 2013. Collaborative brain–computer interfaces for the automatic classification of images. In *6th International IEEE EMBS Conference on Neural Engineering (NER)*, 1096–1099.

Miranda, E. R., and J. Castet. 2014. *Guide to Brain–Computer Music Interfacing*. London: Springer.

Müller-Putz, G. R., C. Breitwieser, F. Cincotti et al. 2011. Tools for brain–computer interaction: A general concept for a hybrid BCI. *Frontiers in Neuroinformatics* 5: 30.

Nam, C. S., J. Lee, and S. Bahn. 2013. Brain–computer interface supported collaborative work: Implications for rehabilitation. In *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 269–272.

Nijholt, A. 2015. Competing and collaborating brains: Multi-brain computer interfacing. In *Brain–Computer Interfaces*, ed. A. E. Hassanien, and A. T. Azar, 313–335. Springer International Publishing.

Nijholt, A., and M. Poel. 2016. Multi-brain BCI: Characteristics and social interactions. In *Proceedings of the 10th International Conference on Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience*, 79–90.

Nijholt, A., B. Reuderink, and D. O. Bos. 2009. Turning shortcomings into challenges: Brain–computer interfaces for games. *Entertainment Computing* 1 (2): 85–94.

Obbink, M., H. Gürkök, D. P.-O. Bos, G. Hakvoort, M. Poel, and A. Nijholt. 2012. Social interaction in a cooperative brain–computer interface game. In *2012 International Conference on Intelligent Technologies for Interactive Entertainment*, 183–192. Springer Berlin Heidelberg.

Philips, J., J. del R. Millán, G. Vanacker et al. 2007. Adaptive shared control of a brain-actuated simulated wheelchair. In *2007 IEEE 10th International Conference on Rehabilitation Robotics (ICORR)*, 408–414. IEEE.

Poli, R., C. Cinel, A. Matran-Fernandez, F. Sepulveda, and A. Stoica. 2013a. Towards cooperative brain–computer interfaces for space navigation. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces*, 149–160. ACM.

Poli, R., C. Cinel, F. Sepulveda, and A. Stoica. 2013b. Improving decision-making based on visual perception via a collaborative brain–computer interface. In *2013 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)*, 1–8. IEEE.

Poli, R., D. Valeriani, and C. Cinel. 2014. Collaborative brain–computer interface for aiding decision-making. *PLoS ONE* 9 (7): e102693.

Schultze-Kraft, R., K. Görgen, M. Wenzel, J.-D. Haynes, and B. Blankertz. 2013. Cooperating brains: Joint control of a dual-BCI. In *Proceedings of the Fifth International Brain–Computer Interface Meeting 2013*.

Stoica, A., A. Matran-Fernandez, D. Andreou et al. 2013. Multi-brain fusion and applications to intelligence analysis. In *Proceedings of SPIE 8756, Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applications*. doi:10.1117/12.2016456.

Townsend, G., and V. Platsko. 2016. Pushing the P300-based brain–computer interface beyond 100 bpm: Extending performance guided constraints into the temporal domain. *Journal of Neural Engineering* 13 (2): 026024.

Valeriani, D., C. Cinel, R. Poli. 2017a. Augmenting group performance in target-face recognition via collaborative brain–computer interfaces for surveillance applications. In *8th International IEEE EMBS Neural Engineering Conference*. IEEE.

Valeriani, D., C. Cinel, R. Poli. 2017b. Group augmentation in realistic visual-search decisions via a hybrid brain–computer interface. *Scientific Reports* (in press).

Valeriani, D., R. Poli, and C. Cinel. 2015. A collaborative brain–computer interface for improving group detection of visual targets in complex natural environments. In *7th International IEEE EMBS Neural Engineering Conference*, 25–28. IEEE.

Valeriani, D., R. Poli, and C. Cinel. 2016. Enhancement of group perception via a collaborative brain–computer interface. *IEEE Transactions on Biomedical Engineering* 64 (6): 1238–1248.

van de Laar, B., H. Gürkök, D. Plass-Oude Bos, M. Poel, and A. Nijholt. 2013. Experiencing BCI control in a popular computer game. *IEEE Transactions on Computational Intelligence and AI in Games* 5 (2): 176–184.

van Erp, J., F. Lotte, and M. Tangermann. 2012. Brain–computer interfaces: Beyond medical applications. *Computer* 45 (4): 26–34.

Vidal, J. J. 1973. Toward direct brain–computer communication. *Annual Review of Biophysics and Bioengineering* 2(1), 157–180.

Wang, Y., and T.-P. Jung. 2011. A collaborative brain–computer interface for improving human performance. *PLoS ONE* 6 (5): e20422.

Wang, Y., Y.-T. Wang, T.-P. Jung, X. Gao, and S. Gao. 2011. A collaborative brain–computer interface. In *2011 4th International Conference on Biomedical Engineering and Informatics (BMEI)*, 583–86. IEEE.

Wolpaw, J. R., N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. 2002. Brain–computer interfaces for communication and control. *Clinical Neurophysiology* 113 (6): 767–791.

Wolpaw, J. R., D. J. McFarland, G. W. Neat, and C. A. Forneris. 1991. An EEG-based brain–computer interface for cursor control. *Electroencephalography and Clinical Neurophysiology* 78 (3): 252–259.

Yuan, P., Y. Wang, X. Gao, T.-P. Jung, and S. Gao. 2013. A collaborative brain–computer interface for accelerating human decision making. In *International Conference on Universal Access in Human-Computer Interaction*, 672–681. Springer Berlin Heidelberg.

Yuan, P., Y. Wang, W. Wu, and H. Xu. 2012. Study on an online collaborative BCI to accelerate response to visual targets. In *Proceedings of the 34th Annual International IEEE EMBS Conference*, 1736–1739. IEEE.

Zioga, P., M. Ma, P. Chapman, and F. Pollick. 2014. A wireless future: Performance art, interaction and the brain–computer interfaces. In *Proceedings of the ICLI 2014—Interface: International Conference on Live Interfaces*, 220–230.