Two Brains, One Game: Design and Evaluation of a Multiuser BCI Video Game Based on Motor Imagery

Laurent Bonnet, Fabien Lotte, and Anatole Lécuyer

***Abstract*—How can we connect two brains to a video game by means of a brain–computer interface (BCI), and what will happen when we do so? How will the two users behave, and how will they perceive this novel common experience? In this paper, we are concerned with the design and evaluation of multiuser BCI applications. We created a multiuser videogame called *BrainArena* in which two users can play a simple football game by means of two BCIs. They can score goals on the left or right side of the screen by simply imagining left or right hand movements. To add another interesting element, the gamers can play in a collaborative manner (their two mental activities are combined to score in the same goal), or in a competitive manner (the gamers must push the ball in opposite directions). Two experiments were conducted to evaluate the performance and subjective experience of users in the different conditions. In the first experiment, we compared a single-user situation with one multiuser situation: the collaborative task. Experiment 1 showed that multiuser conditions are significantly preferred, in terms of fun and motivation, compared to the single-user condition. The performance of some users was even significantly improved in the multiuser condition. A subset of well-performing subjects was involved in the second experiment, where we added the competitive task. Experiment 2 suggested that competitive and collaborative conditions may lead to similar performances and motivations. However, the corresponding gaming experiences can be perceived differently among the participants. Taken together our results suggest that multiuser BCI applications can be operational, effective, and more engaging for participants.**

***Index Terms*—Brain–computer interface (BCI), evaluation, game design, multiplayer games.**

I. Introduction

BRAIN–COMPUTER interface (BCI) technology enables a user to send commands to a computer or other system using only his/her brain activity. The most common way to acquire such physiological signals is by using electroencephalography (EEG): several sensors are placed on the user's scalp to acquire the microcurrents produced by the activity of neurons in the brain. The past decade has seen a widespread enthusiasm for this technology and its potential applications. Many researchers now drift from the original objective, helping disabled people to recover a means of interaction with their environment and surrounding [1], to multimedia applications such as video games [2].

The video game context adds many new challenges for the BCI research community, as both the physical and virtual environments are usually highly complex [3]. Indeed, the typical gamer is a healthy user that may produce a wide range of movements during the gaming experience, most of them disrupting the BCI itself. The virtual environment may also disturb the BCI usage as it produces many distractions: visual, tactile, or auditory stimuli.

In spite of these challenges, video games hold a lot of potential for use in BCIs as they aim to entertain and motivate the users. As the motivation plays a major role in the success of BCI interaction [4], video games thus represent a highly relevant application field for training and mastering BCI systems. Previous studies by Leeb *et al.* [5] or Ron-Angevin *et al.* [6] show how using virtual reality in BCI feedback improves the performances of the system, especially with naive or untrained users. Furthermore, the recent advances in the acquisition technologies, resulting in low-cost EEG devices [7], [8], make the use of BCI feasible in a gaming context outside the laboratories. Multiple studies have already tackled the use of EEG-based BCI in a video game context [9], regarding the interaction techniques and nature of feedback [10], the performances [10], or the subjective experience [11].

In this paper, we focus on a particular interaction paradigm, which is already widely used in gaming in general, but mostly neglected in BCI research so far: the multiuser interaction. The objective is to connect multiple users to the same video game application in real time, through their brain activity.

We address several challenging questions. The first ones are related to the technical feasibility and design of the system itself. We seek to conceive and implement a multiuser BCI system for gaming purposes, which implies merging multiple BCI inputs. A tradeoff must be found between immersion and simplicity for the design of the feedback: while a complex and immersive feedback will be close to a commercial video game, a simpler one with reduced distractions could lower the mental workload, thus facilitating BCI use.

Second, how multiuser interaction differs from single-user control is yet to be studied. Thus, we aim to qualify and quantify the influence of a multiuser paradigm on the BCI interaction, with regards to the performances and user impressions (e.g., motivation or enjoyment).

Therefore, in this paper, we propose three contributions.

- *BrainArena*, a new multiuser BCI video game based on motor imagery (MI). We present its concepts, architecture, and implementation.

Manuscript received April 30, 2012; revised September 18, 2012; accepted November 19, 2012. Date of publication January 01, 2013; date of current version June 10, 2013. This work was supported by the French National Research Agency within the OpenViBE2 project.

L. Bonnet and A. Lécuyer are with the VR4i Team, Inria, Campus Beaulieu, Rennes 35042, France (e-mail: bonnet.lrt@gmail.com; anatole.lecuyer@inria.fr).

F. Lotte is with the LaBRI/Potioc Team, Inria Bordeaux Sud-Ouest, Talence 33405, France (e-mail: fabien.lotte@inria.fr).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TCIAIG.2012.2237173

1943-068X/$31.00 © 2013 IEEE

- The introduction of two paradigms of interaction for multiuser BCI applications: a collaborative mode (i.e., the users share a common goal and a common action) and a competitive mode (i.e., the two users have conflicting intentions, and their actions are opposed).
- An evaluation of our system in these conditions, on 20 naive subjects.

This paper is organized as follows. After reviewing the current state of the art regarding BCI video games, and multiuser interaction and feedback design, we present the *BrainArena* concepts, architecture, and implementation. We then move on to the results and analysis of two evaluations we conducted on 20 naive subjects playing the *BrainArena* BCI game. The first experiment was comparing single-user condition with multiuser condition, whereas the second experiment was focused on collaborative versus competitive situations. Finally, we discuss these results and the potential applications of the multiuser BCI interaction in video games.

II. Related Work

A variety of games using BCI interaction have already been developed. Some use the BCI explicitly as a control channel. In the *MindBalance* [12] game, the player was able to control the balance of his avatar by focusing on two flickering targets triggering different steady-state visual evoked potential (SSVEP) responses. In the application of Lotte *et al.*, *Use the force!* [10], the player was able to lift a virtual spaceship by performing MI of the feet (i.e., imagination of feet movements [13]). The control paradigm used event-related synchronization (ERS) of the Beta rhythm. The Graz-BCI Game Controller developed by Scherer *et al.* [14] was able to connect any BCI or physiological sensor input to a game, using intelligent and context-aware tools. They used the Emotiv software suite to identify users' mental states (e.g., *excitement* or *meditation*) and facial expressions, to control an avatar in the famous online game *World of Warcraft (WoW)*. The Austrian company g.Tec presented the IntendiX Screen-Overlay Control Interface (SOCI) [15] at the CeBIT expo 2012 (Hanover, Germany), that relied on SSVEP to select different items on a screen. Visitors could test it by controlling an avatar in *WoW*. Recent research has also been focused on implicit interaction with video games [16]. Nijholt *et al.* introduced in *AlphaWow* [9] the use of alpha activity to detect the stress level of the player, automatically adapting the avatar's form. *Bacteria Hunt* [17] was a multimodal BCI game based on both explicit and implicit BCI interaction: while the avatar movements were modified by the user stress level (alpha), a target selection was done using SSVEP detection. For a more comprehensive overview of BCI use in video games, the interested reader can refer to [18], [9], and [19].

While researchers were aiming at making BCI interaction possible in a gaming context, the question of multiuser interaction arose. Acknowledging the current trends in video game usage (e.g., network connection, multimodal interaction) Nijholt [20] described his objectives toward a multiparty and social application of BCI in the future. The author foresaw an integration of BCI interaction in our media-based social life (e.g., video games, Internet). A first step toward such multiparty social gaming was presented by Obbink [21], in which the author studied the influence on social interaction of using BCI control (selection using SSVEP) in a two-player game (*Mind the sheep!*). As any cooperative task implies interaction between users, both physical and vocal, this interaction may conflict with the BCI usage itself. EEG systems are prone to muscular artifacts and noise in such situations. The author qualified and quantified the social behaviors between the two players, such as utterances and empathic gestures. He addressed the influence of the BCI on the collaboration level, compared to mouse control condition. However, his paper did not compare performances or preferences of users in multiuser versus single-user scenarios. Blankertz *et al.* reported using the Berlin-BCI system in a two-player environment [22], inspired by the famous video game *Pong*. This application was successfully used during the CeBIT expo 2006 (Hanover, Germany) on two subjects performing demonstrations all day. However, to the authors' best knowledge, there exists no formal description and evaluation of the system.

Another issue of BCI game design is the influence of the feedback presented to the user. The importance of feedback was raised early in the BCI community [23]. Neuper and Pfurtscheller reviewed the trends in BCI feedback [24] and pointed out the effect of feedback during the training phase, and how its nature and computation mode influence future performances. Barbero *et al.* were interested in the feedback accuracy [25]: during a motor-imagery task, participants were presented a biased feedback (strong or weak, positive or negative bias). This study concluded that subjects with low performances benefit from a strong positive bias in their feedback. Designing an appropriate feedback for BCI applications, in general, is still considered as an interesting topic in the community. Introducing BCI interaction in the video game world, where the feedback must be entertaining above everything else, is thus a challenge on its own.

When working on BCI games, another key point is motivation, which plays a major role in any BCI interaction. Nijboer *et al.* studied this topic on severely paralyzed patients suffering from amyotrophic lateral sclerosis (ALS) [4]. The importance of motivation also emerged from the work of Nijboer *et al.* [26], while the authors were designing an auditory-based BCI and evaluating it on disabled subjects. Influence of motivation has also been assessed by Kleih *et al.* on healthy subjects [27]: by raising the motivation level of P300 speller users (with financial incentive), the authors observed an increase in their performance. User acceptance and motivation is usually assessed through questionnaires and subjective appreciation. Plass-Oude Boss *et al.* emphasized the role of user experience evaluation [28] in order to improve further designs of any BCI application, especially in an entertainment context, e.g., video games. This work was extended by Van de Laar *et al.* [29].

We can conclude from the literature that multiuser interaction using BCI control in a gaming application has been introduced only recently, and has not been studied in depth. At present, there has not been any experiment that specifically compares solo and multiplayer MI-based BCI gaming, and how it may influence performance and user experience/preference.

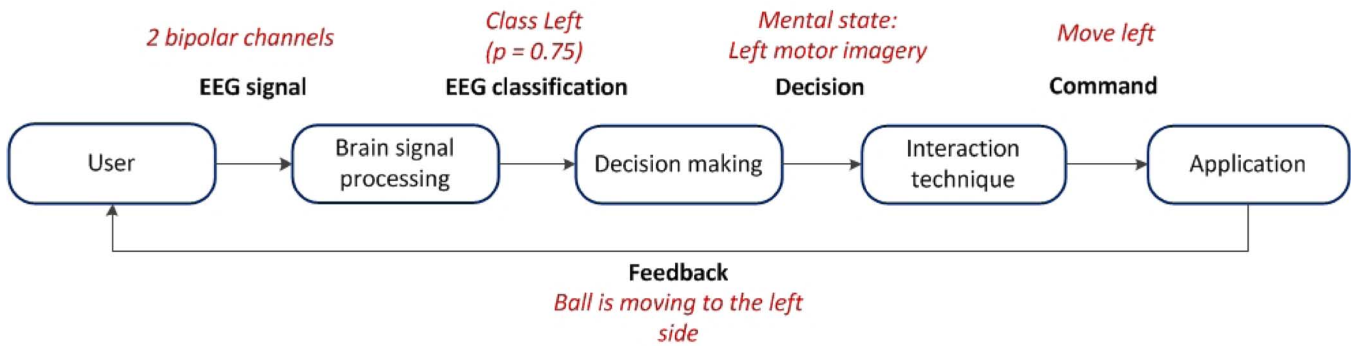


Fig. 1. Single-user BCI interaction loop, illustrated by an example (in red/italic font) inspired by the use of MI paradigm. Two bipolar channels are acquired on users' scalps during a hand MI trial. The signal processing outputs a class label with a probability (e.g., class left with 75% probability). The decision making concludes that the probability is high enough to decide the user's mental state: a left hand MI. In the interaction technique this decision is translated into a command for the application: move left. From this command, the application produces a visual feedback: the ball on screen is moving left.

III. *BrainArena*: A Multiuser BCI Game Based on MI

We designed a multiplayer video game concept called *BrainArena*, a football game controlled by hand MI. The objective of two users is to imagine left or right hand movements to move a virtual ball toward a goal located on the left or right side of the screen, respectively. The design of this application covers a large panel of technical issues: synchronization of the EEG acquisition and processing, EEG signal processing and classification, video game visual rendering, multiuser feedback design, and real-time feedback rendering. The flexibility of our implementation enables easy switching between three different modes: single-user condition and collaborative and competitive multiuser conditions (see Section III-D).

In this section, we first present several definitions of multiuser interactions with video games to contextualize our work. We then move on to the hardware and software components of the *BrainArena* BCI game, and the different game modes developed.

A. Multiuser BCI Interaction With Video Games

A single-user BCI interaction with a video game environment, presented in Fig. 1, is a closed-loop system. The EEG signals are first acquired from a user, then classified by a signal processing unit. The decision maker uses this classification to choose the user's mental state, then the interaction technique (i.e., the system for transforming the interface input data to comprehensible information for the application [30]) uses this decision to produce a command. Finally, the application gives feedback to the user according to the effects of the command.

We consider a situation of *multiuser BCI interaction* when two or more people equipped with a BCI system share an interaction in a common environment. In a gaming context, multiuser interaction is also referred to as *multiplayer* interaction. We can extend this principle to an environment where actors may be indistinctly people, objects, or intelligent systems. This configuration is related to the *multiparty* interaction presented by Nijholt [20].

Multiuser BCI systems can connect users at four different levels in the loop, as illustrated in Fig. 2.

1) At the level of the signal processing system, input EEG signals from several users can be merged to produce a unique multiuser analysis. Offline works of Fallani *et al.* on hyperbrain networks [31] or Astolfi *et al.* on EEG hyperscanning [32] are related to this concept. Example #1 in Fig. 2 illustrates this connection with two users performing MI of the hands, with different EEG setups but a unique classification.
2) At the decision level, the chosen class can be viewed as the result of several classification results. An example could be the combination of different emotional mental states that contribute to deciding the dominant feelings in a viewer group watching a movie or a commercial. Example #2 in Fig. 2 presents the decision making from two MI classifications; the mental state is deduced from the most probable class.
3) At the level of the interaction technique, several dependent decisions can be combined to issue a multiuser command to the application. Cumulating several actions on the same virtual or physical objects is possible. For example, an object can be moved according to two decisions, one for the direction and one for the distance. In Fig. 2, example #3 shows how two decisions (one hand MI mental state for a direction and one SSVEP outcome for a selection) can be joined to produce a unique command.
4) At the level of the application, the feedback can be defined as the result of several independent interaction commands. A simple example would be several users controlling their independent avatars in a virtual world. Example #4 in Fig. 2 uses two separate BCI pipelines that issue different commands based on MI, moving two different objects on screen.

Any multiuser interaction in a video game can also be characterized regarding the objective of the interaction.

- *Independent* multiuser interaction: The users have distinct objectives while interacting with the environment. These objectives are independent and unrelated.
- *Collaborative* multiuser interaction: Two or more users share the same objective. They may choose different actions but their ultimate goal remains the same.
- *Competitive* multiuser interaction: User objectives are in conflict. The goal may be different but ultimately the course of actions collides. Only a subset of users can win.

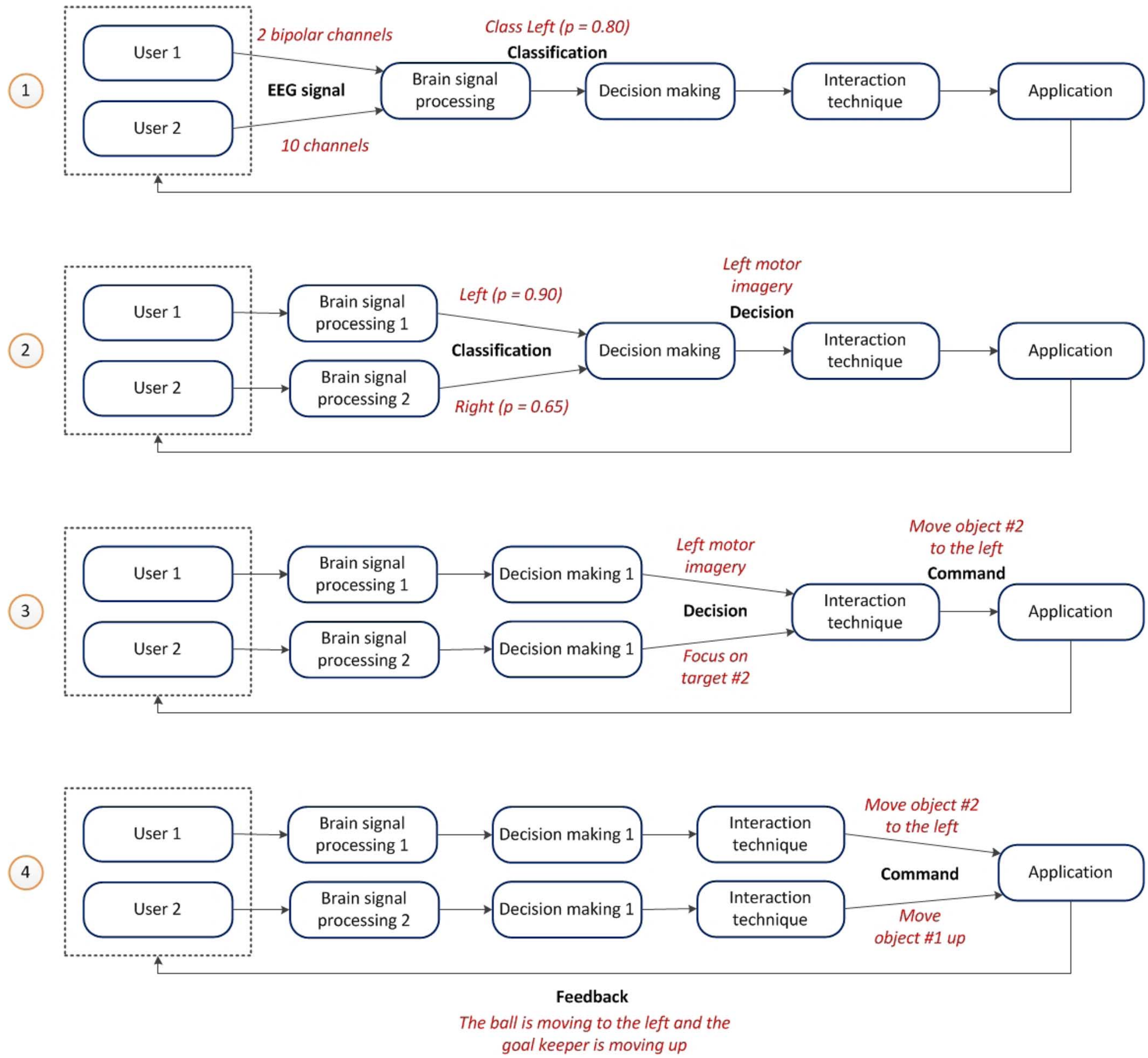


Fig. 2. Four different scenarios of multiuser BCI interactions depending on the user connection level, illustrated by examples in red/italic font. Only the connection level inputs and outputs are described. 1) The EEG signals from two users performing hand MI are merged in the same signal processing that produces a unique classification with a probability (class left with 80% probability). 2) Two hand MI classifications are merged in the decision making, which here simply chooses the most probable mental state between two classes. 3) Two decisions, one hand MI state and one focused target BCI paradigm such as SSVEP, are merged to issue a unique command for the application: move the selected target to the left. 4) Two independent commands issued by two separated MI BCI pipelines are merged into the application to produce a complex feedback where two different objects (a ball and a goal keeper) are moved on a screen.

As the objectives may be multiple in the same situation, collaborative and competitive interactions can both be present in the same context. For example, in a sport video game, with two teams of users, the interaction within the teams is collaborative (e.g., move, pass), but competitive when facing the opposite team members (e.g., score a goal). Even in a fully collaborative game (e.g., two users resolving a puzzle game), a form of competition can always be found if the users define themselves a certain success metric (e.g., number of pieces of puzzle resolved). We predict that competitive behaviors are likely to happen with people experienced at gaming in general, even if the game principles and objectives are not designed as competitive.

The BCI system we present in this paper makes the connection between users at the decision level. Each user has his/her own EEG acquisition and tuned BCI pipeline that outputs a classification (a class label, left or right MI, and a value depending on the classifier result). *BrainArena* uses the two classification results to decide which mental state is dominant and to what extent. In our case, mastering a BCI interface based on MI is known to be difficult for untrained users. Thus, we chose a simple environment with limited distractions.

B. *Architecture*

The architecture of the *BrainArena* BCI game is represented in Fig. 3.

It is composed of several layers:

- *EEG acquisition*: caps and amplifiers acquire the EEG signals of both users in parallel;
- *EEG processing*: EEG signals are processed and classified to identify the user's mental state;
- *Interaction paradigm*: *BrainArena* takes the two BCI processing outputs to decide which is the dominant mental state, and to control the feedback;

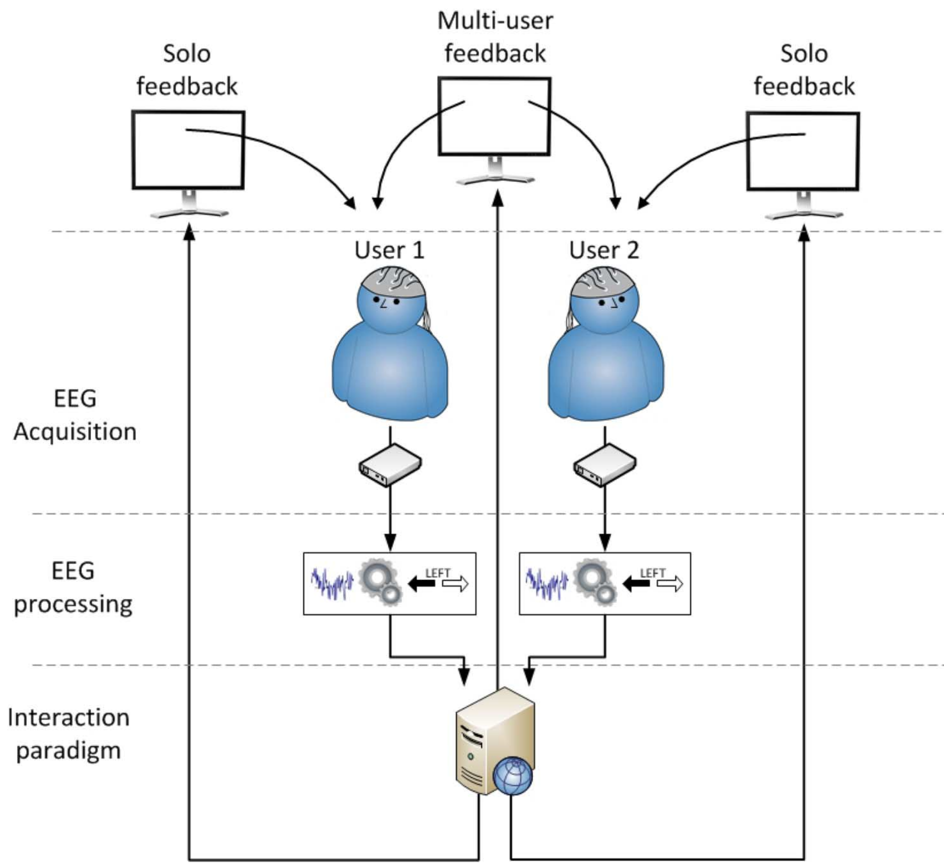


Fig. 3. Architecture of the *BrainArena* multiuser BCI application.

- *feedback*: three possible feedbacks can be displayed according to the game mode (solo, collaborative, competitive).

Our implementation of this architecture relied on three interconnected computers. We assigned the different functions described previously onto these regular desktop computers. The first one acquired the signals from two g.USBAmp amplifiers (g.Tec GMbH, Austria) and GAMMACaps with up to 16 active electrodes. This station also ran the multiuser video game mode when required. The two other stations were assigned to each subject, for the signal processing and the single-user video game mode. The acquisition computer was used as a monitoring station for the experimenter. We based our implementation on the OpenViBE software platform [33] for the EEG acquisition, the signal processing and the output of commands for the external game application, and the interconnection between every software component. The video game programs were written using the Ogre3D rendering engine [34]. A picture of the apparatus is shown in Fig. 4, and Fig. 5 shows the system in use.

C. Video Game Design

The application was designed as a tradeoff between the complexity of the visual feedback and the user's visual workload. We chose a very simple environment to avoid distractions that could disrupt BCI usage. We displayed a ball at the center of the screen on a black background. Goals were symbolized by two triangles on each side of the screen (see Fig. 6 for an annotated screenshot). A green cross could be displayed in the center, with green or blue gauges going left or right during game sessions.

The feedback gave two complementary pieces of information. First, the real-time feedback on the "intensity" of the commands given by the users was provided: a gauge which went left or right depending on whether left or right MI was recognized, and whose length represented the actual intensity of the command. When two users were connected, three gauges were displayed: the two single-user feedbacks plus a multiuser gauge in the middle for the resulting overall command, summing both users' commands. The lengths of the user gauges were directly proportional to the normalized output of the classifier(s) used in the BCI process (see Section III-E). In multiuser modes, the sum of the output was divided by two, so that the resulting multiuser feedback was in the same range as the real-time feedback in the single-user mode. The sizes and directions of the gauges were updated in real time, 16 times per second.

The second form of feedback involved the ball rolling horizontally when pushed by the mental commands (i.e., left or right hand MI), acting like a cumulative feedback for the user. The real-time gauges could be viewed as a representation of these push forces applied to the ball, each push being added to the previous ones to move the ball. The ball had a physics-based behavior, thus when pushed it acquired a velocity. This speed was attenuated by a viscosity parameter which slowed the ball gradually, or by an opposite push. Moving the ball to a given goal was the objective of the game, and increased the users'

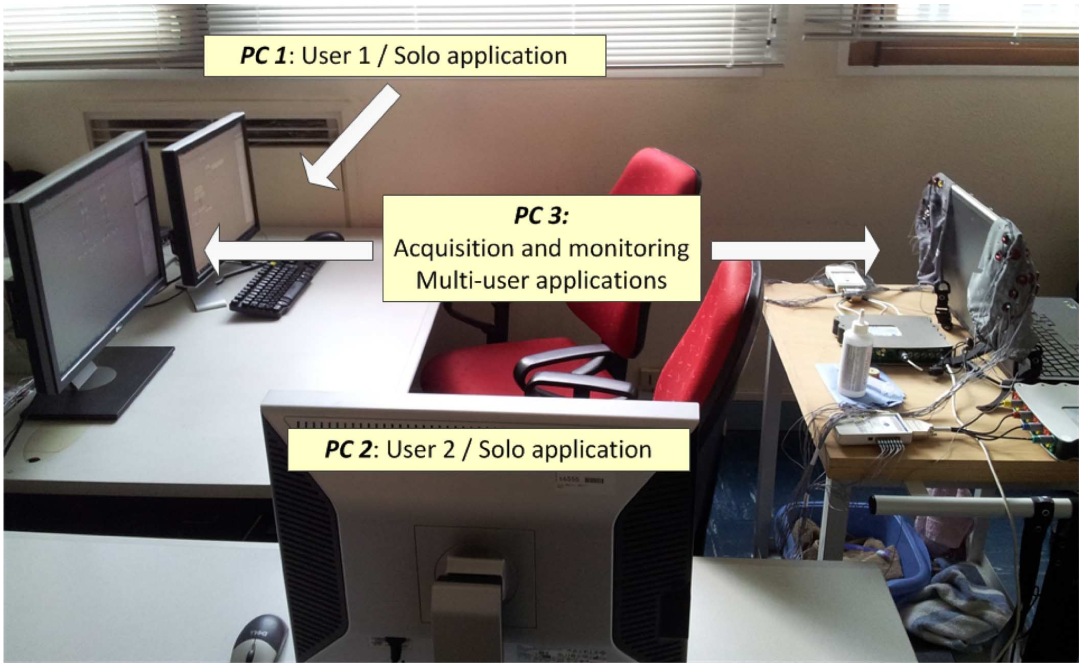


Fig. 4. Experiment apparatus.

scores accordingly. Figs. 7 and 8 present this feedback during collaborative and competitive trials, respectively.

D. Different Paradigms: Solo, Collaborative, and Competitive

We designed three different paradigms: one single-user and two multiuser interactions. The *solo* mode involves only one user, thus one BCI pipeline. The system asks the user to score a goal on the left or right side of the screen, by performing an imaginary movement of the corresponding hand. Fig. 6 presents the application during a *solo* trial. This paradigm was used to compare single and multiuser control in a BCI game.

In multiplayer gaming, people are expected to work together to achieve a goal and/or work against each other to be the best. Thus, we designed two versions of our multiuser BCI game: a collaborative mode, where players are supposed to join forces to achieve the goal and improve their score; and a competitive version where they must perform better than their opponent.

The *collaborative* version (Fig. 7) received inputs from two BCI systems. The two users shared the same objective: moving the ball to the left or right goal. The instruction was displayed for each user beside their name (USER 1 and USER 2; see Fig. 7). The application displayed the gauge feedback of both users. Between users' individual feedbacks, the multiuser feedback was presented in blue as the sum of both feedbacks. The ball was pushed by the multiuser feedback. In this context, scoring a goal could become very challenging as one user performing poorly could easily prevent the ball from reaching the goal. This was confirmed by beta testers before the evaluation. To avoid the frustration that may be created by such a situation, the ball was automatically animated at the end of each trial to reach the nearest goal.

The *competitive* mode (Fig. 8) was similar to the collaborative one except that the instructions given to the two users were opposite. For example, when the first user had to score in the left goal, the second user had to score in the right one. Scoring a goal in this situation was even more challenging. To enhance the competition between users the ball was again animated at the end of each trial, reaching the nearest goal automatically. Thus, one user would always score a goal against the other, at the end of each trial.

E. EEG Signal Processing

Our BCI was built around a classical pattern recognition scheme, which involves the following steps:

1) acquisition of a training data set;
2) training of a subject-specific BCI model, i.e., of subject-specific features and classifiers; more precisely, we used:
    - subject-specific spatial filters obtained with the common spatial pattern (CSP) algorithm [35];
    - a linear discriminant analysis (LDA) as classifier [36], which employs the obtained CSP features as input;
3) online use of the resulting subject-specific model.

During the acquisition of the training set, the user was asked to perform left and right hand MI according to visual instructions (see Section IV for details). A total of 40 training trials were collected for each subject (20 trials from each MI class). Each trial lasted 8 s, the instruction being displayed at $t = 3$ s. The subject had to perform the instructed imaginary hand movement continuously for 5 s.

Once the training data were acquired, they were used to optimize CSP spatial filters. To do so, EEG signals were first band-pass filtered in the mu and beta frequency bands (8–30 Hz). Then, the CSP filters were optimized on these filtered EEG signals, using a 4-s time window extracted from each trial, starting 500 ms after the visual instruction. As recommended in [37], we selected six CSP spatial filters, corresponding to the highest and lowest eigenvalues of the generalized eigenvalue decomposition used to optimize the filters.

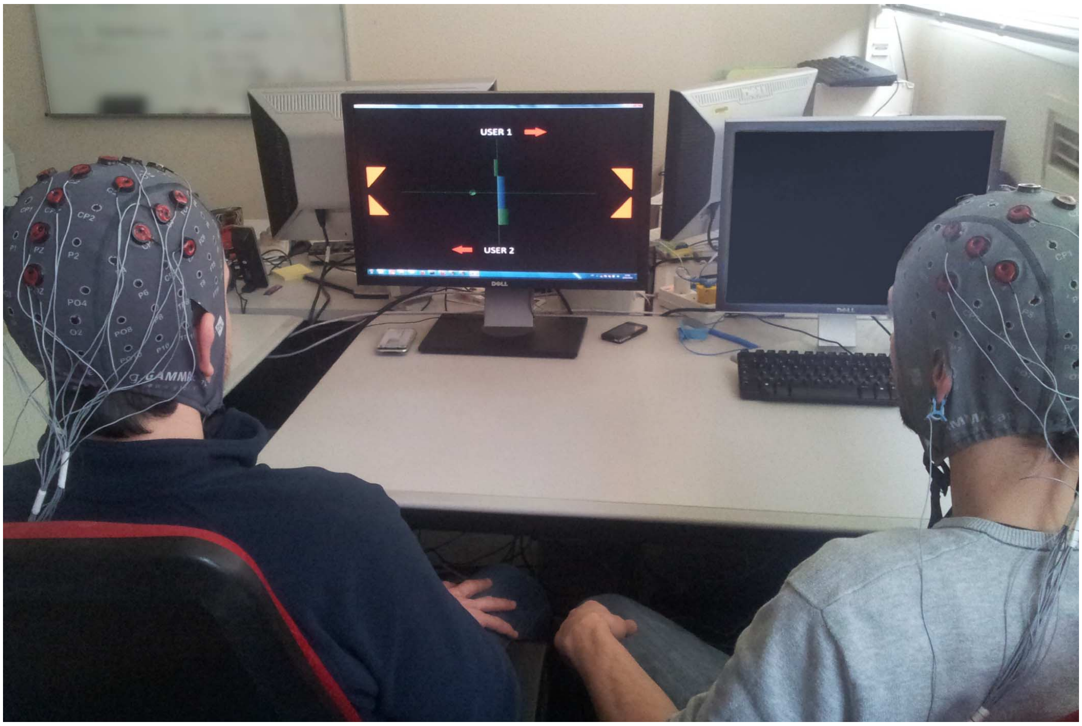


Fig. 5. Two users playing *BrainArena* in a competitive trial.

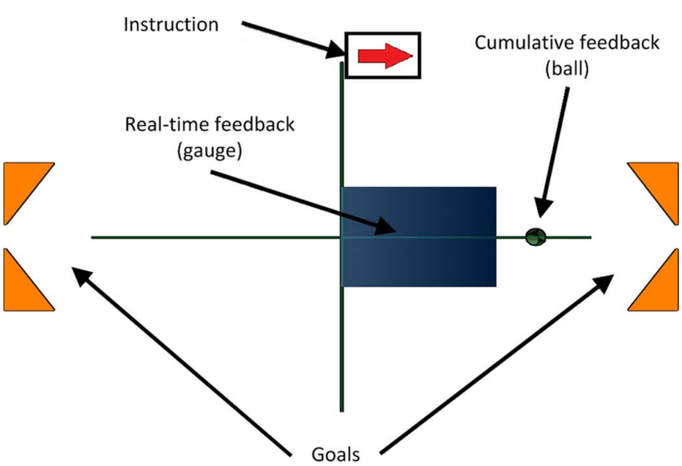


Fig. 6. Single-user mode: The user was instructed to imagine movements of the hands to move the ball into the designated goal. The background is presented here in white for better visibility, however the original configuration uses a black background.

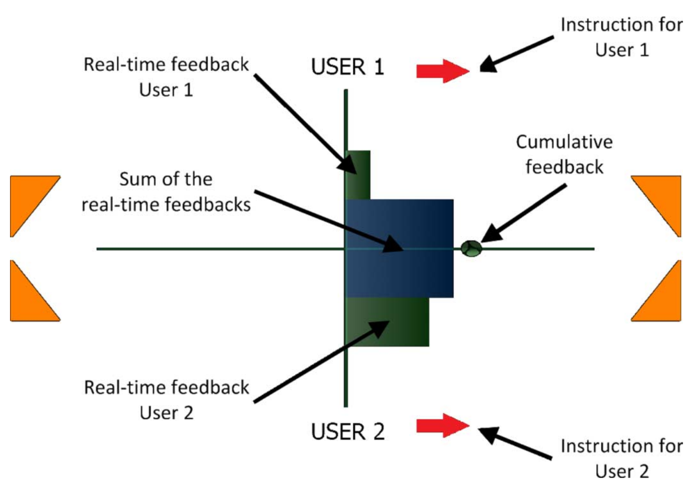


Fig. 7. A collaborative trial: Users should score in the right goal. The background is presented here in white for better visibility.

Once the CSP spatial filters were obtained, they were used to compute input features for the LDA classifier. The features computed were the logarithmic band power widths of the spatially filtered EEG signals in the 8–30-Hz band, averaged over 1 s of signal. To train the LDA classifier, again, a 4-s time window starting 500 ms after the visual instruction was extracted from each trial. Then, each of these 4-s windows was subdivided into 48 1-s segments, with a step of 1/16th of a second (with overlap) between two consecutive segments. A CSP feature vector (as described above) was computed for each of these segments, and labeled according to the trial label (left or right). The resulting 40×48 feature vectors were used as training data for the LDA classifier.

During the online phase, CSP features and the LDA classifier were used to continuously classify the last 1-s segment of EEG signal (with a step of 1/16th of a second, with overlap, between two consecutive segments) into one of the two classes (left or right). Since LDA classification is based on the distance to a separating hyperplane, this distance was normalized and used as the basis of the feedback provided to the users.

This signal processing scheme was applied to each user, each one ending with a specific set of CSP filters and an LDA classifier. The CSP and LDA training was performed before each session. It should be stressed that this EEG signal processing pipeline is independent from the paradigm used for the feedback (single user, collaborative, or competitive). In other words, when more than one user was involved, the same processing was

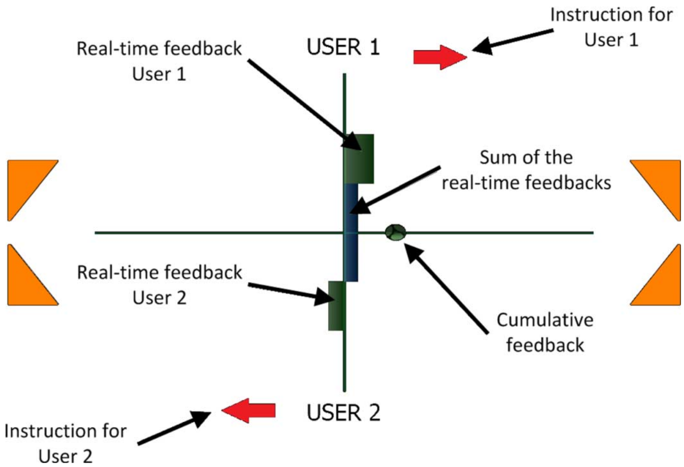


Fig. 8. A competitive trial: Users should score in opposite goals. The background is presented here in white for better visibility.

performed, just that the outputs of each user's EEG processing pipeline (i.e., each user's LDA output) were merged in the game. This decided which mental state was dominant and deduced the commands that produced the feedback.

F. Provisional Conclusion

We designed a complete BCI system for multiuser interaction with a video game. We provided a high level architecture and a first implementation using three general purpose desktop computers (dual cores/4-GB RAM). Fully operational, this system worked in real time: acquisition, EEG signal processing, classification, and feedback rendering. We achieved with our setup a constant frame rate of 60 frames/s. The different components were interconnected on a local network, supporting easily the connection and reconnection of different video game programs. We proposed three different modes for our game: solo, collaborative, and competitive. More versions could be easily developed and connected to the BCI system. Finally, this setup also had monitoring and recording capabilities, thus can be used in an experimental environment for evaluation purposes.

The following sections describe two experimental evaluations we conducted to evaluate the *BrainArena* BCI video game, and the influence of a multiuser gaming experience on the BCI performances and user preferences.

IV. Experiment 1: Comparing Single-User Versus Multiuser Conditions

This experiment evaluated the multiuser and single-user interaction paradigms. We aimed to study the influence of a multiuser situation on the performances and user experience of two users connected through BCI to the same video game program. Only two conditions were selected for this first evaluation: single-user condition (Solo) versus a two-user collaborative condition (Collab).

The classification accuracy during the online sessions was used as a performance metric. The reported performances are the maximal classification accuracy over the trial duration, as done by Graz [38], [35]. Through subjective questionnaires we also compared the user acceptance and enjoyment regarding the two interaction techniques. The questionnaire was divided into two parts. In the first part of the questionnaire, participants rated the two paradigms on a seven-point Likert scale, over several criteria. A second part of the questionnaire intended to gather subjective answers to various questions regarding the tasks and how they handled them, and their impressions on the collaborative task and feedback.

A. Population

The population consisted of 20 volunteers, all of them naive users of BCI technologies. The subjects' age ranged from 23 to 52 years old (mean 31.1), 15 males and five females. From this group, ten pairs were formed. In eight pairs, the participants knew each other, and volunteered to participate together. The two other pairs were formed randomly with the four remaining volunteers.

B. EEG Configuration

The setup for this experiment used the apparatus previously described, with the following configuration. EEG signals were sampled at 512 Hz. We used eight EEG channels located around the right and left motor cortices: C3, FC3, CP3, C1 and C4, FC4, CP4, C2. We assumed that CSP spatial filters can be reliably computed on this number of sensors since Ang *et al.* successfully used it with even fewer sensors (three bipolar channels only) in their winning entry of BCI competition IV, data set 2b [39].

C. Procedure

The procedure was inspired by the Graz BCI [40]. One session consisted of 40 trials, 20 left and 20 right, in a random order. At time $t = 0$, a cross was displayed on screen, marking the start of the trial. At $t = 3$ s, the instruction was displayed as a left or right arrow, instructing the user to perform left or right MI, respectively. At time $t = 4.250$ s, the feedback began to be displayed (only in the online phase, not in the training phase). At time $t = 8$ s, the feedback phase ended. The pause between each trial was randomly chosen between 1.5 and 3.5 s. Each session lasted approximately 8 min. Participants had a 3-min break between sessions.

The experiment consisted of five sessions. The first session was the acquisition of a training set for the CSP filters and LDA classifier. During this first session, no feedback was displayed, only the cross and instructions. The following sessions were either in the Solo or Collab condition (two Solo, two Collab). Preliminary testers reported a better understanding of the instruction if they started in the Solo condition. Therefore, the first session was always in the Solo condition, the condition order for the other sessions being randomly chosen.

Before starting the experiment, we instructed the user on how to perform hand MI. As recommended in [41], we asked the user to perform kinesthetic imagery (feeling the sensations of movement, first person process) rather than visual imagery (seeing yourself doing the movement, third person process).

The whole experiment, installation and explanations included, lasted approximately 90 min.

TABLE I

MEANS OF THE CLASSIFICATION ACCURACY (IN PERCENT) OF EVERY SUBJECTS ON THE FOUR SESSIONS (TWO IN EACH CONDITION). THE WINNER OF EACH PAIR (BEST MEAN OVERALL ACCURACY) IS ANNOTATED WITH A (W), AND THE LOSER IS ANNOTATED WITH AN (L)

	Session 1	Session 2	Session 3	Session 4	Mean SOLO	Mean COLLAB
Pair 1	SOLO	COLLAB	COLLAB	SOLO		
User 1 (W)	90	85	90	82.5	86.25	87.5
User 2 (L)	72.5	60	67.5	67.5	70	63.75
Pair 2	SOLO	COLLAB	SOLO	COLLAB		
User 1 (W)	65	62.5	62.5	77.5	63.75	70
User 2 (L)	62.5	65	57.5	62.5	60	63.75
Pair 3	SOLO	SOLO	COLLAB	COLLAB		
User 1 (L)	80	62.5	65	72.5	71.25	68.75
User 2 (W)	82.5	80	87.5	87.5	81.25	87.5
Pair 4	SOLO	SOLO	COLLAB	COLLAB		
User 1 (L)	80	75	75	70	77.5	72.5
User 2 (W)	77.5	92.5	100	97.5	85	98.75
Pair 5	SOLO	COLLAB	COLLAB	SOLO		
User 1 (W)	70	82.5	75	77.5	73.75	78.75
User 2 (L)	85	70	67.5	57.5	71.25	68.75
Pair 6	SOLO	COLLAB	SOLO	COLLAB		
User 1 (W)	62.5	65	75	70	68.75	67.5
User 2 (L)	62.5	67.5	52.5	50	57.5	58.75
Pair 7	SOLO	COLLAB	COLLAB	SOLO		
User 1 (L)	62.5	62.5	62.5	57.5	60	62.5
User 2 (W)	60	65	70	57.5	58.75	67.5
Pair 8	SOLO	COLLAB	SOLO	COLLAB		
User 1 (L)	75	75	67.5	87.5	71.25	81.25
User 2 (W)	75	85	72.5	82.5	73.75	83.75
Pair 9	SOLO	SOLO	COLLAB	COLLAB		
User 1 (W)	82.5	87.5	87.5	90	85	88.75
User 2 (L)	70	67.5	60	65	68.75	62.5
Pair 10	SOLO	COLLAB	COLLAB	SOLO		
User 1 (W)	72.5	75	77.5	62.5	67.5	76.25
User 2 (L)	80	67.5	72.5	67.5	73.75	70
Means	73.37	72.62	72.25	72.12	**71.25**	**73.94**
Winner (W) subgroup performance					**75.0**	**80.0**
Loser (L) subgroup performance					**67.5**	**67.8**

D. Results

The mean classification accuracies obtained in each condition are displayed in Table I. The mean accuracy for the SOLO condition was 71.3%, while it was 73.9% for the COLLAB condition. This difference was not found to be significant with a paired t-test, although it did show a trend $(p = 0.06)$. Looking at the course of performance over the sessions does not suggest that a learning effect occurred. The average performance curves are indeed rather flat. This is consistent with observations in [42] that suggest that there is no learning on such a small number of sessions.

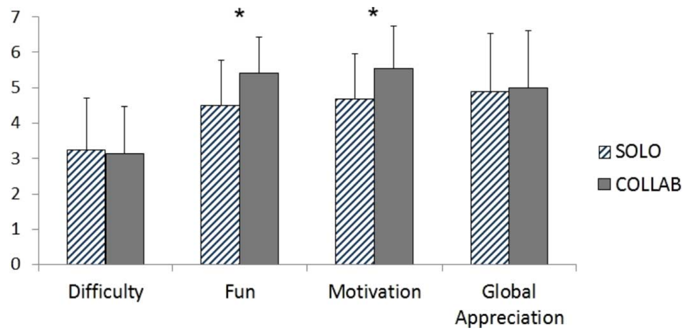


Fig. 9. Means and standard deviations of the quantitative questionnaire grades. A star (*) indicates a significant difference between the two conditions ($p < 0.05$, Wilcoxon signed rank test with Bonferroni correction for multiple comparisons).

We divided the subject pool into two subgroups, according to their performance levels. The *winner* subgroup consisted of the dominant participants of each pair (best mean overall accuracy). The *loser* subgroup was the other half, with the worst mean accuracy of each pair. As shown in Table I, in the *winner* group, the mean classification accuracy in SOLO condition was 75.0%, and 80.0% in the COLLAB condition. This difference was found to be significant with a paired t-test $(p = 0.01)$. The *loser* group showed no significant differences between the two conditions (SOLO: 67.5%, COLLAB: 67.8%).

From the quantitative questionnaires, we extracted the different grades given by the 20 participants. Fig. 9 presents the mean and standard deviation for each criteria:

- difficulty to achieve the task (1: very difficult, 7: very easy);
- fun (1: very boring, 7: very entertaining);
- motivation (1: not motivating at all, 7: very motivating);
- global appreciation (1: poor, 7: very good).

The questionnaire results showed significant differences with a Wilcoxon signed rank test SOLO versus COLLAB, for the motivation and fun criteria ($p < 0.05$ with Bonferroni correction). The differences for the other criteria were not found to be significant.

The subjective questionnaire addressed five themes.

1) *MI strategy*: What was your strategy to successfully achieve the task? Was it different in the two conditions?
2) *Motivation*: Did you find different motivations while performing the experience alone or with a partner?
3) *Impressions on the collaborative feedback*: Did the feedback of your partner influence you? If so, how?
4) *Self-evaluation of the performances*: Did you find yourself better than your partner? Three choices were available: better/equal/worse. Participants were also asked to give details on how and why they felt such a difference.
5) *Preference*: What is your preferred condition, alone or with a partner?

Table II lists the different categories and number of subjects per category. The two major strategies used by the participants involved thinking of simple hand or arm movements. The users reported different motivations when playing the game: “not to impede the other’s performance” or “find a better mental state

TABLE II
DESCRIPTIVE ANALYSIS OF ANSWERS TO POST-HOC OPEN QUESTIONS

Motor imagery strategy	
Arm movement	4
Hand gesture	3
Manipulation of objects from the everyday life	2
Hit a punching ball	2
Push the ball into the goal	2
Others strategies	2

Motivations	
Try not to impede the other's performance	5
Find a better mental state control	5
Achieve the task and score goals	4
Perform better than the other	2
Other/No opinion	2

Impressions toward collaborative feedback	
Neutral: purely informative or no opinion	8
Negative: disturbs the user	7
Positive: helps the user adapting his/her mental state	5

Self-evaluation of the performances	
I performed better than the other	7
We performed equallywell	8
I performed worse than the other	5

Preference	
Single-user condition	10
Collaborative condition	6
No opinion	4

control" incorporated most participants (5/20 participants for both), while others chose more competition-oriented answers (score goals, be better than the other). When asked for their impressions on the collaborative feedback, participants reported negative (7/20 users), neutral (8/20 users), or positive feelings (5/20 users) on whether they found the feedback disturbing, purely informative, or helpful, respectively. While 7/20 participants found themselves better than their partner, 8/20 found no differences and 5/20 felt worse performances. Finally, the preference question showed that 10/20 participants preferred the single-user condition; 6/20 participants preferred the collaborative gaming context.

The user impressions toward the collaborative interaction divided the population into three subgroups: positive perception (76.5% mean classification performance during collaborative sessions), neutral perception (76.7%), or negative perception (68.9%). The performance differences between negative perception and neutral or positive perceptions were found to be significant with a paired t-test ($p < 0.05$). When looking at the classification performance of these three subgroups during single-user sessions, we also found to have significant differences between negative perception (67% accuracy) and neutral (74.7% accuracy) or positive perception (76.5% accuracy).

The mean classification accuracies for the participants that preferred SOLO over COLLAB condition were 70.1% in SOLO sessions and 75.9% in COLLAB sessions. The difference was found to be significant (paired t-test, $p < 0.01$). The subgroup that preferred the COLLAB condition achieved a mean classification performance of 70.1% in the SOLO condition and 69.4% in COLLAB, the difference not being significant.

V. EXPERIMENT 2: COMPARING COLLABORATIVE VERSUS COMPETITIVE CONDITIONS

As observed in experiment 1, the introduction of a multiuser BCI paradigm could influence the motivation and behavior of the participants. In this second experiment, our objective was to qualify more precisely the multiuser experience, and study how the users handle a competitive situation compared to a collaborative one. We kept the best participants from the first experiment and introduced the competitive condition COMPET. We monitored the same metrics as before, i.e., performance and participants' answers to a subjective questionnaire.

A. Population

We selected the eight best performing subjects based on the classification accuracy obtained from experiment 1. Two pairs were already formed during the first evaluation, and the two other pairs were randomly arranged.

B. EEG Configuration

We used the same apparatus, with the following configuration for the EEG acquisition. The amplifiers acquired data at a 512-Hz sampling frequency. In order to try and improve the quality of the CSP filters, we raised the channel number to 16 for each user: C3, C4, FC3, FC4, C1, C2, CP3, CP4, C5, C6, Fz, Cz, FCz, CPz, Pz, and POz.

C. Procedure

This experiment was divided into seven sessions. The first session was the training session, made of 40 trials (20 left, 20 right in a random order). The six following sessions consisted of two random sequences of three sessions, from each of the three conditions (SOLO, COLLAB, and COMPET). These six sessions were shorter than in the previous evaluation (30 trials, 15 left and 15 right in a random order) to limit the overall duration of the experiment. The complete experiment lasted approximately 105 min.

D. Results

The classifier accuracy was computed for each user using the same procedure as in the first evaluation. The mean classification accuracy values of the three conditions for the eight subjects can be found in Table III.

There was no significant difference between the collaborative and competitive conditions (COLLAB: 75,4%; COMPET: 74,6%). This suggests that using a competitive context rather than a collaborative one may not lower the performance achieved by the users. We separated each pair to form the *winner* and *loser* subgroups, as we did in Section IV-D. The *winner* groups achieved classification accuracies of 77.5% in SOLO, 81.67% in COLLAB, and 79.58% in COMPET. The *loser* group showed inverse tendency with 74.17% in SOLO, 69.17% in COLLAB, and 69.58% in COMPET. However, none of these differences were significant, which can be partially explained by the small number of subjects.

TABLE III
MEANS OF THE CLASSIFICATION ACCURACY (IN PERCENT) OF EACH SUBJECT DURING THE THREE EXPERIMENTAL CONDITIONS. THE WINNER OF EACH PAIR (BEST MEAN OVERALL ACCURACY) IS ANNOTATED WITH A (W), AND THE LOSER IS ANNOTATED WITH AN (L)

	SOLO	COLLAB	COMPET
Pair 1 User 1 (W)	78.333	76.67	90
Pair 1 User 2 (L)	66.67	70	68.33
Pair 2 User 1 (W)	78.33	83.33	88.33
Pair 2 User 2 (L)	78.33	71.67	90
Pair 3 User 1 (W)	78.33	76.67	75
Pair 3 User 2 (L)	81.67	70	55
Pair 4 User 1 (L)	70	65	65
Pair 4 User 2 (W)	75	90	65
Means	**75.83**	**75.42**	**74.58**
Winner (W) subgroup performance	**77.5**	**81.67**	**79.58**
Loser (L) subgroup performance	**74.17**	**69.17**	**69.58**

TABLE IV
USER CATEGORIES AND NUMBER OF SUBJECTS PER CATEGORIES, FOR EVERY QUESTIONNAIRE THEME

Motor imagery strategy	
Focus on the mental imagery	4
Adapt the mental state by analysing the situation	4

Motivations	
Perform better than the other	3
Achieve the task and score goals	2
No opinion	3

Impressions toward multi-user feedback	
Neutral: purely informative or no opinion	1
Negative: disturbs the user	3
Positive: helps the user adapting his/her mental state	4

Self-evaluation of the performances	
I performed better than the other	2
We performed equally	5
I performed worse than the other	1

Preference	
Collaborative condition	4
Competitive condition	4

The means and standard deviations of the questionnaire grades are presented in Fig. 10. Once again fun and motivation showed better results with the two multiuser conditions than with single-user interaction. There was no significant difference after Bonferroni correction.

Finally, the subjective questionnaires were analyzed to classify the user on the same thematics as in experiment 1: strategy, motivations, impressions toward multiuser feedback, self-evaluation of performances, and preferences.

The strategies used were separated in two categories (4/8 participants per category): self-centered (focus on the mental imagery) or context-based (analyze the situation and adapt the

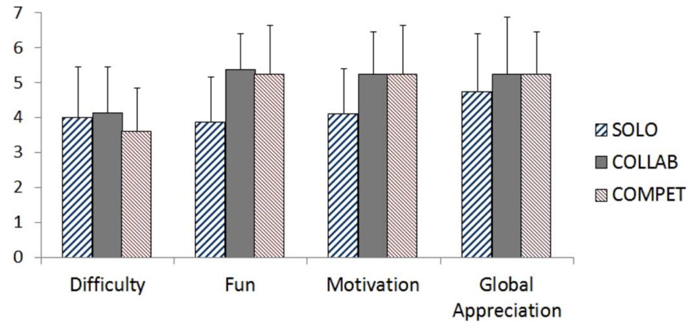


Fig. 10. Means and standard deviations of the quantitative questionnaire grades.

mental state). The motivations were either competitive (3/8 users) or focused on achieving the task and scoring goals (2/8 users); 4/8 users found the multiuser feedback helpful, and 3/8 users were disturbed by it. Most of the users (5/8 participants) found their performances equal to that of their partner. Finally, the users equally preferred the competitive and collaborative conditions. None preferred the single-user condition.

This second experiment represents a reliable basis to acknowledge trends, however it is done on a rather small number of subjects. In order to confirm these trends, experiments on more subjects are necessary.

VI. DISCUSSION

The *BrainArena* BCI game was functional in experimental conditions. The system managed to handle EEG signal processing and feedback rendering in real time. The mean classification performances over all users were above 70% in all conditions. The two experiments we conducted on the *BrainArena* BCI game allow us to evaluate the influence of the multiuser interaction on users' performance and subjective impressions.

The first evaluation on 20 naive subjects compared the single-user situation with the multiuser situation using the collaborative condition. Although the mean classification performance was not significantly better in the collaborative condition, it showed a tendency ($p = 0.06$), which will have to be confirmed in further studies. However, when analyzing separately the best performing users and the worst performing ones from each pair, we found a significant difference between collaborative and single user for the best performing user only. This means that operating a BCI in a multiuser context is possible without any performance drop, and may even increase the classification performances of the best performing users. The 7/20 participants that found the collaborative feedback disturbing reported, for example: *"Too much information to handle..."* or *"it's moving too fast, it disturbs my concentration."* As this user group performed poorly in both conditions (67% in single user, 68.9% in collaborative) we can assume that they could not handle the visual stimuli even in the single-user condition. The users' self-evaluation of performances showed unbalanced results. More participants found themselves better than their partner, compared to those who found themselves worse (seven and five participants, respectively). They were right in both cases if we look at their placement in the *winner/loser* classification. However, five participants could not perceive the difference of performance, even when this difference was high. For example, user 1 of pair 6 perceived equal performances while he outclassed his partner by 10%. This can be interpreted as another evidence of the difficulty in understanding and evaluating the collaborative feedback. These results offer several ideas of improvement in order to make the *BrainArena* BCI game more user friendly: e.g., smoothing the real-time feedback to lower the disturbance, or extending the trial duration to give users the time to understand what is going on.

As the quantitative questionnaires revealed, motivation and enjoyment showed significant differences in favor of the collaborative mode. Difficulty and global appreciation were not statistically different. Thus, we can assume that a multiuser interaction can be controlled with the same level of difficulty as a single-user interaction. However, the user preferences showed surprising results: ten subjects preferred the single-user condition and only six the collaborative one. Additionally, those who preferred playing in a single-user condition performed better during the collaborative task, while the subjects that preferred the collaborative task showed no differences in performance between the two conditions. This can be interpreted in different ways. First, we could simply assume that user preferences are not only dependent on the performances achieved, but also on the enjoyment and motivation to do the task. Second, several users preferred the single-user condition just because they were, in that case, the only cause of success or failure. The most common motivation raised in the questionnaire was *"I don't want to impede my partner"* or *"Understanding and finding a better control strategy"* (five users in both categories). Even if they performed better in the collaborative mode, they still preferred a condition which they solely controlled. A third interpretation could be related to the link between task complexity and efforts required to achieve the task. As the collaborative task is found more complex, the user must focus more intensively, which therefore ensures higher performance. However, when asking for a preference, the users turned to the simplest task: the single-user game mode. This also applies to the second group who preferred the collaborative condition: as they handled the complexity of the collaborative task well, their efforts are on a similar level in both conditions, which leads to similar performances.

This first evaluation highlights the complex relation between user impressions, difficulty of the task, feedback understanding, and performance. The user preferences are not only related to their performances or motivations to do the task. The psychology plays an important role, and even more when two users are interacting within the same context. As the user impressions show, the effects of multiuser may be negative (e.g., *"I felt very frustrated when I didn't manage to help my partner," "I was totally discouraged when I saw the other going on the other side"*) or positive (e.g., *"good to have someone to help when we don't manage one side, "it's better to laugh together when we make mistakes than being frustrated when we fail alone"*). We see a high variability in the users behavior and subjective impressions.

The second evaluation was conducted on a smaller subset made of the best participants. As they only participated in four sessions in the first evaluation, we cannot qualify them as trained users, but we assume their first experience made it easier to handle the task in one more multiuser condition : the competitive mode.

When asked for their strategy to perform the mental imagery task, all participants naturally took a higher level of abstraction: they tried either to *"focus on the mental imagery"* or *"analyze the context and adapt their mental state."* In the previous evaluation, they were mostly focused on doing the hand mental imagery or arm, or manipulating an object. This group of subjects is characterized by a competitive spirit, revealed in the questionnaires: the users only reported being motivated by *"scoring goals"* or *"being better than the other."*

The classification results in the three conditions showed no significant difference (75.83% in single user, 75.42% in collaborative, and 74.58% in competitive). All these results have to be interpreted with care, as the limited number of subjects questions the relevance of further statistical analysis: additional experiments should be evaluated to further confirm our results. The quantitative questionnaire results also revealed no differences between the three conditions. This result suggests that using a competitive condition over a collaborative one does not affect the motivation and enjoyment of the users. While performances remain the same in the three conditions, the preferences go clearly in the multiuser direction: half the subjects preferred the collaborative task, and the other half the competitive condition. None of them preferred the single-user condition. This further reveals that users' preferences are not only related to the performance achieved.

As the second experiment uses a reduced number of subjects (eight subjects, four pairs), future work should include larger experiments to evaluate the collaborative versus competitive conditions in order to make stronger conclusions.

The user impressions toward the multiuser feedback were very variable and contrasted. Further research could be focused on finding the best feedback concept. Such feedback should be understood easily by all users, allowing them to accurately evaluate their performance without giving them too much disturbance. The tradeoff may be very dependent on users, and finding new adaptation techniques, supervised or not, would be useful.

The *BrainArena* multiuser BCI game gives every user the same ability to control the application. Thus, disabled people could play such a game together with healthy users with less or identical frustration. Such multiuser BCI systems could provide a new way of communication and interaction between a patient and his/her relatives, based on entertainment.

VII. Conclusion

In this paper, we have studied the design and evaluation of a multiuser BCI video game called *BrainArena*. This video game application is based on hand MI, and allows two users to simultaneously play a simple football game. The players can use left (or right) imagined hand movements to push a ball toward the left (or right) goals. A collaborative mode enables players to push together in the same direction, whereas a competitive mode enables users to play a duel and try to push in opposite directions. The *BrainArena* video game was evaluated on 20 subjects in a first experiment that compared single-user and multiuser collaborative conditions. The eight best performers participated in a second experiment where we added the multiuser competitive condition. Our results show first that our multiuser video game is fully operational and that our different scenarios can be rapidly handled by participants. Motivation and fun were strongly increased in multiuser conditions. Interestingly, the performance of the "winners" (people who performed better than their partner) was found to increase in multiuser versus solo conditions, suggesting a potential benefit of a multiuser approach. Some interesting psychological factors or behaviors are also exhibited. When two users are playing the same BCI game, specific feelings of frustration, hesitation, shyness, or irritability could occur. This opens possibility for further work, where behavioral studies could benefit from BCI game design.

In these two experiments, most of the participants (16/20 subjects) knew each other and volunteered together. This proportion does not make possible any statistical analysis, however this would be interesting to study if and to what extent this could influence the motivations and performance of the users in the different conditions. On a broader scale, multiuser BCI design, for video gaming purposes or not, could also benefit from sociological studies on team design, collaboration, and motivation among teams, and how these can influence task performance. For example, Harrison *et al.* addressed how deep-level relationships between team members can influence performance [43]. For a review on team performances and especially on the factors that influence team performance, the interested reader can refer to [44].

We focused our study on the classification performances and the user experience. In future work, it would be interesting to conduct further analysis from a neuroscience perspective, e.g., by comparing the event-related synchronization and desynchronization (ERS/ERD) [45] between the different conditions.

Taken together our results pave the way to new designs and new evaluations of multiuser BCI applications.

REFERENCES

[1] J. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, and T. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

[2] A. Lécuyer, F. Lotte, R. Reilly, R. Leeb, M. Hirose, and M. Slater, "Brain-computer interfaces, virtual reality and videogames," *IEEE Computer*, vol. 41, no. 10, pp. 66–72, Oct. 2008.

[3] F. Lotte, "Brain-computer interfaces for 3D games: Hype or hope?," presented at the Found. Digit. Games, Bordeaux, France, Jun. 2011.

[4] F. Nijboer, N. Birbaumer, and A. Kübler, "The influence of psychological state and motivation on brain-computer interface performance in patients with amyotrophic lateral sclerosis a longitudinal study," *Front. Neurosci.*, vol. 21, no. 4, 2010, DOI: 10.3389/fnins.2010.00055.

[5] R. Leeb, F. Lee, C. Keinrath, R. Scherer, H. Bischof, and G. Pfurtscheller, "Brain-computer communication: Motivation, aim, and impact of exploring a virtual apartment," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 4, pp. 473–482, Dec. 2007.

[6] R. Ron-Angevin and A. Daz-Estrella, "Brain-computer interface: Changes in performance using virtual reality techniques," *Neurosci. Lett.*, vol. 449, no. 2, pp. 123–127, 2009.

[7] Emotiv, Apr. 2012 [Online]. Available: http://www.emotiv.com/researchers/

[8] Neurosky-research, Apr. 2012 [Online]. Available: http://www.neurosky.com/Academics/Research.aspx

[9] A. Nijholt, D. P.-O. Bos, and B. Reuderink, "Turning shortcomings into challenges: Brain-computer interfaces for games," *Entertain. Comput.*, vol. 1, no. 2, pp. 85–94, 2009.

[10] F. Lotte, Y. Renard, and A. Lécuyer, "Self-paced brain-computer interaction with virtual worlds: A quantitative and qualitative study, "out of the lab"," presented at the 4th Int. Brain-Computer Interface Workshop Training Course, Graz, Austria, 2008.

[11] D. P.-O. Bos, M. Poel, and A. Nijholt, "A study in user-centered design and evaluation of mental tasks for BCI," in *Advances in Multimedia Modeling*, ser. Lecture Notes in Computer Science, K.-T. Lee, W.-H. Tsai, H.-Y. Liao, T. Chen, J.-W. Hsieh, and C.-C. Tseng, Eds. Berlin, Germany: Springer-Verlag, 2011, vol. 6524, pp. 122–134.

[12] E. Lalor, S. P. Kelly, C. Finucane, R. Burke, R. B. Reilly, and G. McDarby, "Brain-computer interface based on the steady-state VEP for immersive gaming control," *Biomedizinsche Tecknik*, vol. 49, pp. 63–64, 2004.

[13] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.

[14] R. Scherer, M. Proll, B. Allison, and G. Müller-Putz, "New input modalities for modern game design and virtual embodiment," in *Proc. IEEE Virtual Reality Workshops*, Mar. 2012, pp. 163–164.

[15] g.Tec Medical Engineering GmbH, "Press release: Intendix-soci: g.tec introduces mind-controlled computer gaming at cebit 2012," Austria, Mar. 2012.

[16] L. George and A. Lécuyer, "An overview of research on "passive", brain-computer interfaces for implicit human-computer interaction," presented at the Int. Conf. Appl. Bionics Biomech.Workshop W1, Brain-Computer Interfacing and Virtual Reality, Venise, Italy, 2010.

[17] C. Muhl, H. Gürkök, D. P.-O. Bos, M. Thurlings, L. Scherffig, M. Duvinage, A. Elbakyan, S. Kang, M. Poel, and D. Heylen, "Bacteria hunt: A multimodal, multiparadigm BCI game," in *Proc. Enterface Workshop*, 2009, pp. 41–62.

[18] A. Lécuyer, F. Lotte, R. Reilly, R. Leeb, M. Hirose, and M. Slater, "Brain-computer interfaces, virtual reality, and videogames," *Computer*, vol. 41, no. 10, pp. 66–72, Oct. 2008.

[19] D. P.-O. Bos, B. Reuderink, B. van de Laar, H. Gürkök, C. Mühl, M. Poel, A. Nijholt, and D. Heylen, "Brain-computer interfacing and games," in *Brain-Computer Interfaces*, ser. Human-Computer Interaction, D. Tan and A. Nijholt, Eds. London, U.K.: Springer-Verlag, 2010, pp. 149–178.

[20] A. Nijholt, "Towards multimodal, multi-party, and social brain-computer interfacing," in *Proc. 4th Int. ICST Conf. Intell. Technol. Interactive Entertain.*, Genoa, Italy, 2012, pp. 12–17.

[21] M. Obbink, H. Gürkök, D. P.-O. Bos, G. Hakvoort, M. Poel, and A. Nijholt, "Social interaction in a cooperative brain-computer interface game," in *Proc. 4th Int. ICST Conf. Intell. Technol. Interactive Entertain.*, Genoa, Italy, 2012, pp. 183–192.

[22] B. Blankertz, M. Krauledat, G. Dornhege, J. Williamson, R. Murray-Smith, and K.-R. Mller, "A note on brain actuated spelling with the Berlin braincomputer interface," in *Universal Access in Human-Computer Interaction. Ambient Interaction*, ser. Lecture Notes in Computer Science, C. Stephanidis, Ed. Berlin, Germany: Springer-Verlag, 2007, vol. 4555, pp. 759–768, DOI: 10.1007/978-3-540-73281-5-83.

[23] J. Wolpaw, N. Birbaumer, W. Heetderks, D. McFarland, P. Peckham, G. Schalk, E. Donchin, L. Quatrano, C. Robinson, and T. Vaughan, "Brain-computer interface technology: A review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, Jun. 2000.

[24] C. Neuper and G. Pfurtscheller, "Neurofeedback training for BCI control," in *Brain-Computer Interfaces*, ser. The Frontiers Collection, B. Graimann, G. Pfurtscheller, and B. Allison, Eds. Berlin, Germany: Springer-Verlag, 2010, pp. 65–78.

[25] A. Barbero and M. Grosse-Wentrup, "Biased feedback in brain-computer interfaces," *J. NeuroEng. Rehabil.*, vol. 7, no. 1, p. 34, 2010.

[26] F. Nijboer, A. Furdea, I. Gunst, J. Mellinger, D. J. McFarland, N. Birbaumer, and A. Kübler, "An auditory brain-computer interface (BCI)," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 43–50, 2008.

[27] S. Kleih, F. Nijboer, S. Halder, and A. Kübler, "Motivation modulates the p300 amplitude during BCI use," *Clin. Neurophysiol.*, vol. 121, pp. 1023–1031, 2010.

[28] D. P.-O. Bos, H. Gürkök, B. v. van der, F. Nijboer, and A. Nijholt, "User experience evaluation in BCI: Mind the gap!," *Int. J. Bioelectromagn.*, vol. 13, no. 1, pp. 48–49, Jul. 2011.

[29] B. van de Laar, H. Gürkök, D. P.-O. Bos, F. Nijboer, and A. Nijholt, "Perspectives on user experience evaluation of brain-computer interfaces," in *Universal Access in Human-Computer Interaction. Users Diversity*, ser. Lecture Notes in Computer Science, C. Stephanidis, Ed. Berlin, Germany: Springer-Verlag, 2011, vol. 6766, pp. 600–609.

[30] A. Lécuyer, "Using eyes, hands, and brain for 3D interaction with virtual environments: A perception-based approach," University of Rennes 1, Rennes, France, Jun. 2010.

[31] F. De Vico Fallani, V. Nicosia, R. Sinatra, L. Astolfi, F. Cincotti, D. Mattia, C. Wilke, A. Doud, V. Latora, B. He, and F. Babiloni, "Defecting or not defecting: How to read human behavior during cooperative games by EEG measurements," *PLoS ONE*, vol. 5, no. 12, 2010, e14187.

[32] L. Astolfi, J. Toppi, F. De Vico Fallani, G. Vecchiato, S. Salinari, D. Mattia, F. Cincotti, and F. Babiloni, "Neuroelectrical hyperscanning measures simultaneous brain activity in humans," *Brain Topography*, vol. 23, pp. 243–256, 2010.

[33] Y. Renard, F. Lotte, G. Gibert, M. Congedo, E. Maby, V. Delannoy, O. Bertrand, and A. Lécuyer, "Openvibe: An open-source software platform to design, test and use brain-computer interfaces in real and virtual environments," *Presence, Teleoper. Virtual Environ.*, vol. 19, no. 1, pp. 35–53, 2010.

[34] Ogre3d-open source 3d graphics engine, Apr. 2012 [Online]. Available: http://www.ogre3d.org/

[35] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 4, pp. 441–446, Dec. 2000.

[36] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain-computer interfaces," *J. Neural Eng.*, vol. 4, pp. R1–R13, 2007.

[37] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. Müller, "Optimizing spatial filters for robust EEG single-trial analysis," *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 41–56, Jan. 2008.

[38] A. Schlogl, F. Lee, H. Bischof, and G. Pfurtscheller, "Characterization of four-class motor imagery eeg data for the BCI-competition 2005," *J. Neural Eng.*, vol. 2, no. 4, p. L14, 2005.

[39] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition iv datasets 2a and 2b," *Front. Neurosci.*, vol. 6, no. 39, 2012, DOI: 10.3389/fnins. 2012.00039.

[40] G. Pfurtscheller, C. Neuper, G. Muller, B. Obermaier, G. Krausz, A. Schlogl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Wortz, G. Supp, and C. Schrank, "Graz-BCI: State of the art and clinical applications," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 1–4, Jun. 2003.

[41] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller, "Imagery of motor actions: Differential effects of kinesthetic and visual motor mode of imagery in single-trial EEG," *Cogn. Brain Res.*, vol. 25, no. 3, pp. 668–677, 2005.

[42] A. Kübler, D. Mattia, H. George, B. Doron, and C. Neuper, "How much learning is involved in BCI-control?," presented at the Brain-Computer Interface (BCI) Meeting, 2010, poster.

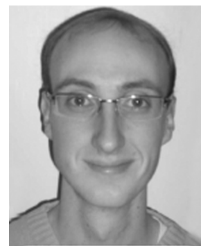
[43] D. A. Harrison, K. H. P. ans Joanne, H. Gavin, and A. T. Florey, "Time, teams, and task performance: Changing effects of surface-and deep-level diversity on group functioning," *Acad. Manage. J.*, vol. 45, no. 5, pp. 1029–1045, 2002.

[44] E. Salas, N. Cooke, and M. Rosen, "On teams, teamwork, and team performance: Discoveries and developments," *Human Factors, J. Human Factors Ergonom. Soc.*, vol. 50, no. 3, pp. 540–547, 2008.

[45] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.

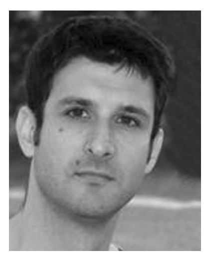
Laurent Bonnet received the M.Eng. degree in software engineering from the National Institute of Applied Sciences (INSA), Rennes, France, in 2009.

He joined Inria, Rennes, France, in 2009, as an Expert Engineer and worked on the development of OpenViBE, the open-source software platform for BCI research, of which he was the Lead Software Engineer between 2011 and 2012. He is a Senior Developer at Mensia Technologies, a software startup company providing real-time, quantitative EEG solutions based on the OpenViBE software. His research interests include brain–computer interfaces (BCIs), virtual reality, and EEG-based human–computer interaction.



Fabien Lotte received the M.Sc., M.Eng., and Ph.D. degrees in computer sciences from the National Institute of Applied Sciences (INSA), Rennes, France, in 2005 and 2008, respectively. His Ph.D. dissertation, dedicated to brain–computer interfaces (BCIs) and virtual reality, received both the 2009 Ph.D. dissertation award from the French Association for Pattern Recognition (AFRIF) and the 2009 Ph.D. dissertation award (2nd prize) from the French Association for Information Sciences and Technologies (ASTI).

He is a Research Scientist at Inria Bordeaux, Talence, France. His research interests include BCIs, virtual reality and 3-D interaction, pattern recognition, and signal processing. In 2009 and 2010, he was a Research Fellow at the Institute for Infocomm Research (I2R), Singapore, working in the Brain–Computer Interface Laboratory.



Anatole Lécuyer received the M.Eng. degree from Ecole Centrale de Lille, Lille, France, in 1996 and the Ph.D. degree in computer science from the University of Paris XI, Paris, France, in 2001.

He is a Senior Researcher at Inria, Rennes, France. His research interests include virtual reality, haptic interaction, and brain–computer interfaces (BCIs). He has been involved as Coordinator or Principal Investigator in various national or international projects such as: ANR projects "OpenViBE1" (2005–2009) and "OpenViBE2" (2009–2012) on Brain–Computer Interfaces and Virtual Reality; the European Strep project "NIW" (2008–2011) on Augmented Walking; and the European Network of Excellence "INTUITION" (2005–2008) on Virtual Reality. He serves as an expert in virtual reality and BCI for public bodies such as the European Commission (EC) or French National Research Agency (ANR).

Dr. Lécuyer is an Associate Editor of the *ACM Transactions on Applied Perception* (ACM TAP) and the *International Journal of Human–Computer Studies* (IJHCS).