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Human Learning for Brain–Computer Interfaces

11.1. Introduction

BCIs are defined by Wolpaw [WOL 02] as tools of communication and control that allow users to interact with their environment by means of their cerebral activity alone. This definition highlights one fundamental aspect of BCIs, the interaction between two components: the user's brain and the computer. The challenge is to make sure that these two components (brain and computer) "understand each other", and adapt to each other so that the system performance (often measured using the accuracy rate) is optimal.

Thus, the working architecture of a BCI [WOL 02] contains a loop with two major stages, after the user sends a command via cerebral activity (which we shall denote stage 0). During stage I, the computer attempts to *understand* the command sent by the user, generally by extracting relevant information followed by classification. Next, during stage II, it is the user's turn to attempt to *understand* the meaning of the feedback generated by the computer, which indicates how the computer understood the command that it received. To see how this loop works, consider the case of a standard BCI protocol in motor imagery [PFU 01]. In this protocol, users can perform two motor imagery tasks, "imagine moving the left hand" and "imagine moving the right hand",

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which are associated with two distinct commands. To provide guidance to the user, the system also produces feedback, often in the form of a bar indicating the task recognized by the system. The direction of the bar depends on the task recognized by the system (e.g. the bar points left if the task "imagine moving the left hand" is recognized). The size of the bar also depends on the value of the classifier output (i.e. higher values indicate that the classifier is more confident in the task recognition, and so the bar will be larger) (see Figure 11.1, left-hand side). In this example, stage I of the loop is the computer's recognition of the motor imagery task performed by the user (is the user imagining moving his left hand, or his right hand?). Then, in stage II, the user now has to understand the feedback generated by the system (what does this bar mean? Did the system correctly recognize the task that I performed? If so, how confident was it?). Unfortunately, it appears that most current systems do not properly establish this mutual understanding, which might explain why users perform poorly when attempting to control the BCI, as well as the non-negligible fraction (between 15% and 30%) of users that find themselves completely incapable of controlling these systems [ALL 10].

How can we facilitate this understanding? Over the last several years, there have been many studies on stage I of the loop: how the computer should understand the task performed by the user. Signal processing algorithms and techniques of machine learning have been developed to achieve this. But two fundamental factors for improving BCI performance have not yet been sufficiently explored:

– *Stage 0, the quality of the signals generated by the user*: for the classification algorithms to be effective (i.e. in order that they can be capable of recognizing motor imagery tasks by extracting specific features from the cerebral signal), the user must be able to generate a *stable* cerebral signal each time that he/she performs the same task, and *distinct* cerebral signals when the tasks are different. These two elements are non-trivial skills, and require a learning process that is both specific and adapted. This is rarely taken into account in BCI training protocols [NEU 10].

– *Stage II, user comprehension of the feedback produced by the system*: The standard BCI protocols often provide the user with feedback in the form of a graphical representation of the classifier output (e.g. the bar described above). Although this is informative (and more importantly allows evaluation/correction), this feedback does not explain to the user why a certain task was or was not recognized, and even less what the user must do in order to improve performance. In a recent review [LOT 13], Lotte *et al*. show that to be effective feedback must provide an explanation (rather than just the possibility of correction), be multimodal (and not just visual), and finally be clear and explicit (which is not the case with classifier output for non-experts).

These different ideas highlight a point that might allow user performance to be improved: facilitating the acquisition of skills by providing adapted learning protocols. As we will see in this chapter, establishing a learning protocol requires various different elements to be taken into consideration: the instructions/indications given to the user, the learning environment, the practice tasks given to the learner and the feedback provided after performing the various different tasks.

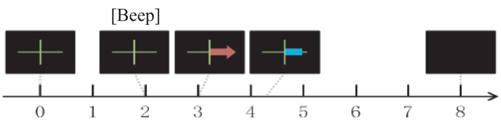
In section 11.2, we will explore the limitations of the standard protocols widely used by the BCI community. Next, we will analyze the learning protocols that have been suggested for BCIs. We will focus on protocols developed for teaching users how to use BCIs based on mental imagery (MI), also known as spontaneous BCIs. Indeed, this is the category of BCI for which the learning process is the most important. Finally, in section 11.4, we will present possible avenues for improving learning protocols, in particular based on an "anthropocentric" perspective. Before we begin, however, let us describe two *historical* approaches that were used with BCIs, on which most of the current learning protocols are based. One protocol was suggested by researchers in Graz [PFU 01] based on techniques of *machine learning*, and the other was suggested by the researchers at the Wadsworth center [WOL 00] based on an *operant conditioning* approach.

11.2. Illustration: two historical BCI protocols

Principle of the Graz protocol [PFU 01]: This approach is organized into two stages: I: training the system; II: teaching the user. In stage I, the user is instructed to successively perform a certain series of MI tasks (for example imagining movements of the left and right hands). Using the recordings of cerebral activity generated as these various MI tasks are performed, the system attempts to extract characteristic patterns of each of the mental tasks from the signal (see Chapter 7). These extracted features are used to train a *classifier* whose goal is to determine the *class* to which the signals belong (i.e. imagining a movement of the left hand or the right hand) (see Chapter 12). This classifier is then typically adjusted over the course of the learning session so that variations in the disposition of the apparatus or in the user conditions between sessions are taken into account. When this stage is complete, stage II involves training the user. The user is instructed to perform the MI tasks, but this time feedback (based on the learning performed by the system in stage I) is provided to inform him or her of the MI task recognized by the system and the corresponding confidence level of the classifier. The user's goal is to develop effective *strategies* that will allow the system to easily recognize the MI tasks that the user is performing.

Definitely, this learning protocol is generally organized over multiple sessions, each of which is composed of sequences (often called *runs*) lasting approximately 7 min. Each session generally has four to six sequences to avoid fatigue, which is often observed after the sixth sequence. Finally, the sequences themselves are divided into trials. One sequence contains 10–20 trials per class (i.e. per MI task) depending on the number of classes. A trial typically lasts for 8 s, during which time a cross appears on the screen followed by a sound to attract the user's attention, further followed by an arrow symbolizing the instruction (e.g. an arrow pointing to the left corresponds to the instruction "imagine moving the left hand") and then visual feedback shown as a bar indicating the recognized task and the corresponding confidence interval of the classifier (e.g. a blue bar pointing to the left means that the system recognized the task of imagining a movement of the left hand; the length of the bar indicates the confidence of the classifier in the recognition of the MI task). The detailed chronology of a trial is shown in Figure 11.1(left).

Principle of the Wadworth center protocol for one-dimensional (1D) cursor control: the BCI system suggested by the Wadsworth center team is based on controlling the sensorimotor rhythms μ and β after a learning process based on operant conditioning [WOL 00]. The initial version of this BCI system, which has now become standard, featured a cursor (or ball) on the screen moving continuously from the left to the right of the screen, at constant speed. The user can control the vertical position of the cursor by modulating the amplitude of his or her sensorimotor rhythms. On the right-hand side of the screen, several targets (generally between two and four, represented by rectangles) are shown, aligned vertically, one by one. The user must adjust the vertical position of the cursor using the BCI so that the cursor hits the indicated target when it reaches the right-hand edge of the screen (see Figure 11.1(right)). This kind of BCI, based on operant conditioning, does not impose any specific mental task on the user, unlike the BCI approach from Graz, nor does it make use of machine learning. Users must find the strategy that allows them to effectively modulate their cerebral rhythms to move the cursor across the screen, on their own. Typically, users utilize motor imagery tasks at the beginning of the learning process, but with practice they report that they use these motor imagery tasks less and less [WOL 00]. Learning to control the BCI takes time, generally several days, weeks or even months of practice. This principle has nonetheless enabled certain users to master controlling a cursor with this BCI in 1D [WOL 00], two dimensions (2D) [WOL 00], and more recently even three-dimensions (3D) [MCF 10]. Notably, this approach was used in the renowned study by Birbaumer *et al.* [BIR 99] published in *Nature* in 1999.



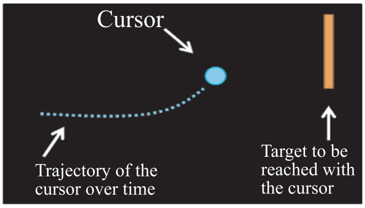


Figure 11.1. *Left: Chronology of a trial: at the beginning of the trial, a cross appears at the center of the screen; after 2 s, a sound is played to indicate that the instruction is imminent; at 3 s, an arrow appears for 1.25 s: the direction of the arrow indicates the MI task that should be performed; at 4.25 s, the feedback is shown for 4 s, and is generally updated 16 times per second depending on classifier output. Right: schematic illustration of a learning trial with the Wadsworth center protocol [WOL 00]*

11.3. Limitations of standard protocols used for BCIs

It has been shown that the standard protocols do not follow the suggested guidelines for learning processes, in particular those suggested by experts in the psychology of learning [LOT 13]. But can we be sure that this has a tangible impact on the user performance when controlling a BCI? Indeed, many other issues have been raised with BCIs, including material problems (e.g. EEG: low signal/noise ratio, variable impedance over time), software problems (e.g. imperfect classification algorithms), and even neurophysiological problems (e.g. non-stationarity of signals). So how can we assess the real impact of learning procedures on BCI performance? In an attempt to answer this question, we used a standard BCI learning protocol [PFU 01] to teach users how to perform a series of simple motor tasks [JEU 14] in a setting without BCIs, and therefore free of all of their associated problems. Over the course of the experiment, users learned how to draw circles and triangles on a digital drawing tablet. Using the same principle as BCI learning, they were instructed to identify the correct strategy (size of the drawing and speed of execution) that allowed the system to recognize the task that they were performing. The results of this study show that, even if the majority does learn and improve over the course of the sequences, 15% of participants obtain accuracy rates of approximately 50% (which is due to randomness, and therefore means that they did not manage to learn to perform these simple motor tasks). This percentage is close to the rate of "illiteracy" in BCIs [ALL 10], which suggests that these protocols are not perfectly adapted to allow users to acquire skills. This result proves the benefit of improving learning protocols with the objective of optimizing BCI performance.

11.4. State-of-the-art in BCI learning protocols

This section offers a review of the literature on existing BCI learning protocols with the objective of establishing guidelines that will be useful for the development of future BCI learning protocols.

11.4.1. *Instructions*

Very few studies have examined the instructions given to users learning to control a BCI. Yet this is a central element of the learning process, since these instructions help users to understand their tasks. Often, these instructions consist only of a single directive indicating that the goal of the exercise is to move the cursor/bar in the right direction. However, as pointed out by Lotte *et al*. [LOT 13], the ultimate objective of the learning protocol is not to move the bar, but to help the user to learn to generate a stable, specific signal for each of the MI tasks that he or she performs. It seems therefore that the learning objective should be made more explicit. One study shows that prompting users to attempt kinesthetic imagination of movements (i.e. to imagine performing the motion, feeling the same sensations, without actually moving anything) rather than simply visual imagination improves the performance [NEU 05]. On the other hand, another study shows that the users that obtained the best performances were those who were not given any specific strategy at the beginning of the learning process [KOB 13]. The authors reason that the success of the learning process depends on subconscious learning mechanisms, and that users who attempt to follow a strategy overload their cognitive resources (which does not result in a positive performance improvement).

11.4.2. *Training tasks*

Although most BCI learning protocols only used one single type of task, which is repeated identically multiple times, a few studies have explored a more varied selection of different tasks. In particular, McFarland *et al.* successfully implemented a progressive sequence of tasks; with operant conditioning, they taught users to first of all control a 1D cursor separately in three different dimensions, then in 2D (for each pair of dimensions), and finally in 3D [MCF 10]. Vidaurre *et al.* experimented with adaptive training tasks by giving subjects a BCI that was initially generic in nature (i.e. independent of the subject, calibrated with the data from multiple other subjects), then progressively more and more adapted to the new user (by adapting the choice of sensors and classifier to this user) [VID 10]. This progressive and co-adaptive approach (the user adapts to the machine and the machine adapts to the user) allowed users that were "illiterate" at first to eventually succeed in controlling the BCI. In a less formal and systematic setting, Neuper *et al.* also explored the idea of allowing the user to learn freely and asynchronously from time to time, with positive results [NEU 03]. Even though this approach has not been compared with the traditional approach (synchronous only), this nonetheless suggests that organizing free-access and asynchronous sessions can be beneficial to BCI learning processes. Finally, Eskandari *et al.* taught their users to meditate before using a BCI, and demonstrated that this had a positive impact on the performance [ESK 08].

11.4.3. *Feedback*

In the standard learning protocols [PFU 01], feedback is given in the form of a bar or a cursor shown on screen, whose direction depends on the task recognized by the classifier and whose size is proportional to the confidence of the classifier in the recognized task. Some studies have suggested other variants for displaying feedback. First of all, Kübler *et al.* [KÜB 01] developed a process that displays a smiley face after each successful trial. In their own study, Leeb *et al.* [LEE 07] replaced the cursor with a gray smiley face that moves toward the left or the right depending on the classifier output. After each trial, the smiley face becomes green and happy if the trial is successful, sad and red if not. This study showed that increasing the motivation levels of users is linked to improved performance. However, neither of these studies offered a formal comparison with the standard feedback process, which makes it impossible to affirm that these kinds of feedback are more effective.

Although the feedback described above (all of which was visual in nature) is simple to implement and intuitive, its effectiveness is not optimal for BCIs. Indeed, it is a recognized fact that in situations of real-life interactions, visual channels are often overloaded [LEE 13], which prompted certain researchers to consider providing feedback via the other senses. Accordingly, several experiments were performed to evaluate the effectiveness of auditory feedback. In the same way as the standard visual feedback, the auditory feedback provided usually represents the classifier output: instead of varying the size of a bar, the classifier output is represented by variations in the frequency of the sound [GAR 12], or its volume [MCC 14], or tone [HIN 04, NIJ 08]. For example, with their *auditory BCI*, Nijboer *et al.* [NIJ 08] used the sounds of two different instruments to indicate the recognition of each of the MI tasks. Although its utility has been proven for patients suffering from locked-in syndrome [SMI 05], because this syndrome is often linked with visual deficiencies and a loss of sensitivity, the performance achieved with auditory feedback has generally been significantly inferior to the performance achieved with visual feedback. One suggested explanation is that it is less intuitive, and thus is longer and more difficult to learn. Also, for real-life applications in open environments (e.g. navigating a wheelchair), the auditory channel is very frequently used and must remain available (much like the visual channel). These factors suggest that auditory feedback is not ideal for applications involving navigation or general entertainment.

Given this context, tactile feedback may have many advantages. First, the sense of touch is very infrequently used for interactions. So, sending additional information via this channel will have little or no effect on the workload [LOT 13], and so will not affect performance. Second, unlike visual and auditory feedback, tactile feedback is personal, and is not perceived by others in the user's immediate environment. Motivated by this, various different types of tactile feedback were tested with BCIs. For example, the feedback can be sent in the form of vibration whose frequency changes as a function of the recognized MI task [CHA 07]. Using a single vibrotactile stimulator on the biceps, it is possible to feel whether the recognized task is an imagined movement of the left hand or the right hand. This study also shows that the performance for a given MI task (MI left hand or right hand) improves when the motor is placed on the same side as the task. This result throws back to the theory of *control-display mapping* [THU 12], which states that the effectiveness of tactile feedback depends on its coherency with the recognized MI task (e.g. stimulate the right hand when a MI task of the right hand is recognized). Other studies [KAU 06, CIN 07, CHA 12, LEE 13] suggest using multiple stimulators to provide feedback to the user. These studies focus in particular on applications with disabled users. The stimulators are placed on the neck or higher back (where sensitivity is preserved). Various different stimulation patterns based on the principles of *control-display mapping* are used as feedback, such as variations in the intensity or the spatial localization. In a recent study [JEU 15b], we tested a *continuous* tactile feedback system for the first time (continuous in the sense that it was updated four times per second), comparing it to an equivalent visual feedback system. We used gloves equipped with five vibrotactile stimulators each: a vibration in the left (or right) hand indicated recognition of the task "imagine moving the left (or right) hand". Furthermore, since we wanted to evaluate the relevance and effectiveness of these two types of feedback (visual and tactile) in interactive contexts, we added a *gamified* task of counting visual distraction elements in the learning environment. Our results show that the performance (combined scores for motor imagery tasks and counting) of users receiving tactile feedback was higher than that of users receiving visual feedback. This study suggests that tactile feedback might be able to increase BCI performance, especially for interactive tasks. However, despite the fact the performance obtained with tactile feedback is often equivalent to that obtained with visual feedback, and sometimes even better [JEU 15b], and also generally provides a better user experience (in that it is considered more natural), the sense of touch has only been infrequently used for BCIs.

Finally, two other very specific types of feedback have been explored. Two studies [KAC 11, WIL 12] examined the application of electrotactile tongue stimulation. The tongue possesses receptors that allow an excellent resolution in space, and sensitivity is preserved even with damage to the spinal column. Two other studies [GOM 11, RAM 12] examined proprioceptive feedback (i.e. feedback that provides information about the position of different body parts and the force required to perform a movement) while operating a neuroprosthesis. These studies produced very good results, showing that proprioceptive feedback coupled with visual feedback produces an improvement in performance compared to only visual feedback. However, these methods are very expensive and invasive, and so are not suitable for general purpose applications.

In addition to using different senses, changes in the content of the feedback have also been investigated. For instance, Hwang *et al.* [HWA 09] suggested training based on neurofeedback. The feedback was represented in the form of a schematic map showing the various activated zones of the cortex in real time, which allowed users to improve their performance. Another study [KAU 11] shows that increasing the level of required attention by using multiple senses does not decrease the performance compared to traditional feedback. Although these approaches are promising, they have not yet been thoroughly explored.

Finally, some studies used a procedure that introduced a bias into the feedback (i.e. by leading users to believe that their performance was better than it actually was). For example, [BAR 10] showed that expert users were hindered by biased feedback, but that this procedure could sometimes prove useful to new users. Another result showed that uniquely positive feedback reduced the performance when used for a large number of sessions [KÜB 01]. These results suggest that the experience level of the user needs to be taken into account when designing the optimal feedback system.

11.4.4. *Learning environment*

Most types of feedback used with BCIs (in particular visual feedback systems) often trigger a decrease in user motivation and are generally associated with an average user experience. *Gamified* learning protocols were developed with the objective of maintaining motivation levels and improving the user experience. For example, McCraedie *et al*. [MCC 14] suggested two simple games based on the *ball–basket paradigm* (i.e. maneuvering a ball to pass through a basketball hoop) and the concept of a spaceship that must avoid asteroids. Other studies, summarized in a review by Lécuyer *et al.* [LÉC 08], even suggested gamified BCI learning protocols that integrated elements of virtual reality. In one of the games, the "use the force" application inspired by Star Wars allows users to levitate a spaceship by imagining moving their feet. Indeed, studies by Ron-Angevin and Díaz-Estrella [RON 09] and Leeb *et al*. [LEE 06] show that using fun protocols, in particular protocols based on virtual reality, an increase in performance is observed for controlling BCIs compared to traditional learning protocols. Although these protocols are effective, they all use feedback that is visual in nature. However, as we have seen, the visual channel is often overloaded in interactive situations for which BCIs might be useful. It would therefore certainly be productive to combine these learning environments with tactile feedback systems, as in the study by Jeunet *et al*. [JEU 15b], and then compare the performance with learning situations in traditional environments.

11.4.5. *In summary: guidelines for designing more effective training protocols*

In this section, we will provide a summary of the guidelines that arise from the studies presented above, the objective of which is to act as a guide for whoever wishes to implement more effective training protocols:

– *Instructions*: it appears to be necessary to explicitly specify the learning objective to the user, in particular the fact that the user must learn to generate a stable, specific signal when performing the different MI tasks in order to be able to control the BCI in the long term. Furthermore, it is important to allow users to experiment independently rather than imposing any particular strategy for performing the tasks. On the other hand, for motor imagery, it appears that kinesthetic motor imagery is more effective than visual motor imagery;

– *Training tasks*: providing tasks that are designed to include a progression (increasing difficulty) and that are adaptive (specific to each user) appears to facilitate the acquisition of BCI-related skills. Including free-access and asynchronous sessions and preparatory practice tasks (e.g. meditation) also seems to help;

– *Feedback*: even though this has not been formally shown in a study, visual feedback with emotional connotations (e.g. smiley faces) seems to increase user motivation levels and consequently their performance. However, visual feedback is not ideal in interactive situations. The same is true for auditory feedback, which does not appear to be truly beneficial except for patients suffering from locked-in syndrome. Tactile feedback is promising, so long as the principles of *control-display mapping* are observed. Indeed, tactile feedback generally produces a level of performance equivalent to visual feedback, but relies on a channel that is much less saturated in interactive situations. Finally, increasing the quantity and the quality of the information provided (e.g. topography of cerebral activity) seems to be useful, as well as adapting the way that the feedback is presented to the experience level of the user;

– *Learning environment*: several studies have shown that gamified learning, especially including elements of virtual reality, increases the user motivation, and consequently performance.

11.5. Perspectives: toward user-*adapted* and user-*adaptable* learning protocols

The previous section presents the work performed until now toward the goal of improving BCI learning protocols. Indeed, we saw that certain studies attempted to build motivation in the learning environment (using games and virtual reality), but that improving the quality of the instructions and the relevancy of the practice tasks and the feedback provided to the user is also important. This review of the literature allows us to observe that the large majority of the work performed on improving BCI training protocols is situated within a larger trend that may be described as *technocentric*. In other words, the objective is to improve the BCI performance by modifying the learning protocols, but all efforts are concentrated on technological aspects (improving the interface and the content of the information provided to the user during learning). In this last section, we will present an emerging perspective in BCIs that may be described as *anthropocentric*, which breaks with but also complements the traditional approach presented above. It is based on a perspective of learning according to which individuals possess personal characteristics, inherited from past experiences, from their culture and thus encoded into their cognitive profile, their personality, etc. Improving

BCI learning therefore occurs by adapting the learning protocols to the personal characteristics of each learner.

This perspective came about from the observation that there is a large amount of variability in BCI studies in terms of performance. It is often the case that with the same learning protocol, certain subjects only achieve performances of approximately the random success rate, whereas others achieve almost 100% success. The question of *why do certain subjects succeed in learning when others fail?* is a legitimate question. This question recently inspired a study [JEU 15a] during which (1) participants were asked to learn to use a BCI based on performing 3 mental tasks (imagine moving the left hand, mental rotation and mental subtraction) [FRI 13] using a traditional protocol [PFU 01] over six sessions (performed over the course of 6 days) and (2) certain aspects of their cognitive profiles and personality were assessed using a selection of different questionnaires. This study produced two major results. The first result is that there is a strong correlation between a *mental rotation* trial score [VAN 78] and the average user performance at MI tasks. This initial observation suggests many interesting perspectives for BCI learning. Indeed, it is possible to imagine learning protocols during which the users' spatial skills are progressively improved, until they can successfully perform MI tasks. Second, the results of the study suggest that it may be possible to establish a model that allows the BCI performance to be predicted from three personality factors: (1) the stress or anxiety level of the user, (2) the user's abstraction/imagination skills and (3) the user's level of autonomy within a group. Similarly to the previous result, this approach provides a framework for a number of promising perspectives for implementing learning protocols adapted to the personal characteristics of the user.

This idea that learning protocols might be adapted to the characteristics of the learner leads us to consider solutions that were developed in the domain of *intelligent tutoring systems* (ITSs) [NKA 10]. ITSs are adaptive computer systems whose purpose is to support the learning of certain concepts by adapting the protocol to the user. An ITS provides sequences of exercises that allow the user to acquire a certain skill. The benefit of ITSs is that (1) this sequence of exercises is *adapted to the profile of the learner* and (2) this sequence is *adaptable during the learning process to match the state of the learner*. Before the learning sequence is started, the system first determines the learner's profile in order to provide a suitably adapted learning protocol (for example determining whether the learner is more *visual* or *verbal*, and providing exercises that are either picture-based or text-based accordingly). The learning process also adjusts to account for the progression of the learner's skill level (i.e. the learner's cognitive state). An increasing amount of effort has been invested in evaluating the progression of learners' emotional and mental states during the learning process. Certain emotions (such as enthusiasm or disappointment) are considered "academic emotions" [PEK 02], as they play a role in the success (or failure) of the learning process. Various indicators can be used to measure these states: behavioral (mouse movements, posture, facial expressions), physiological (variations in heart rate, electrodermal response or breathing) and neurophysiological (modifications of certain cerebral rhythms, measured by EEG). All of these states are objectified with the goal of adapting the exercise sequence in real time, and thus improving the efficiency of the learning process. For example, if an evaluation of the cognitive state finds that certain skills have not been acquired, the system will return to exercises that are designed to reinforce these skills. Similarly, if a decrease in the learner's motivation or enthusiasm is observed and the skills appear to have been acquired, the difficulty of the exercises can be increased more rapidly than was initially planned. ITS-supported learning (just like BCI learning) is a remote learning process: the learner is alone in front of a computer. But it is an established fact that *social presence* is an important factor in improving the efficiency of a learning process [GUN 95]. It has been shown that learning in the presence of a teacher, or other people, even passive observers, leads to an improvement in performance. This is the main reason why *virtual learning companions* (VLCs) were developed in connection with ITS. These VLC, often displayed on the ITS interface, can be configured to provide different kinds of feedback (social presence, emotional or cognitive support) depending on the profile and the state of the learner.

The idea of an ITS specifically designed for BCI learning seems promising, but raises a series of questions. For example, learning mathematics involves determining a sequence of competencies to be acquired, ranging from simple competencies (adding numbers) to more elaborate ones (performing operations on fractions). Defining a sequence of competencies to be acquired in BCI learning has proven to be much more complex. Another unique aspect of BCI learning is that learners are immobile during the learning process, which limits the number of behavioral indicators available for judging the learners' emotional and motivational states. Although these questions still require answers, we can easily imagine a simplified version of an ITS for BCI learning composed of several stages. First, the learner's profile must be characterized. To achieve this, the factors that we know *a priori* are involved in BCI performance (i.e. levels of stress, autonomy, imagination) must be evaluated. A VLC could then provide feedback that is adapted to this profile. For example, it could provide emotional support to anxious subjects, or a social presence to subjects with low "autonomy" scores. Next, using the participants' scores on the Mental Rotation trial, a sequence of exercises of progressively increasing difficulty could allow users to learn to improve their spatial skills, which, together with the support provided by the VLC, should have positive consequences on their BCI performance.

11.6. Conclusions

This chapter gives an idea of the current state of research of BCI learning protocols. The BCI community now recognizes that in order to achieve an improvement in performance, the user must be included in the loop, and so learning protocols must be improved accordingly. We have seen that a few promising avenues regarding the various constituent elements of these learning protocols (instructions, training tasks, feedback and learning environments) have been explored. Unfortunately, these types of study remain few and far between and, critically, their results are insufficiently utilized by the BCI community. We have also shown that by building on theories in disciplines such as the psychology of learning, it is possible to suggest new, promising approaches for improving user performance. One of the most important steps seems to be making the effort of understanding how each user works cognitively in order to offer learning protocols adapted to their individual profiles.

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