Why current human training approaches for Brain-Computer Interfaces are Wrong and How to solve this

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Abstract

Brain-Computer Interfaces (BCI) enable users to send commands to computers using brain activity only. Although promising, BCI remain barely used outside laboratories, due to their low reliability. BCI users learn to produce stable brain activity patterns which the computer recognizes, using signal processing. Most BCI research is focused on signal processing, thus neglecting human training. Based on a study of educational research papers, we argue that current human training approaches for BCI are highly inappropriate. We point out the flaws in training protocols and propose new directions theoretically expected to efficiently train users to control BCI, hence improving their reliability.

Author Keywords

Brain-Computer Interfaces (BCI), ElectroEncephaloGraphy (EEG), feedback, instructional design

ACM Classification Keywords

H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.; H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces, Theory and methods.; H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces, Training, help and documentation.; H.1.2 [Models and principles]: User/Machine Systems, Human factors.

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General Terms

Human Factors

Introduction

Brain-Computer Interfaces (BCI) are communication systems that enable users to send commands to a computer by using only their brain activity, this activity being generally measured using ElectroEncephaloGraphy (EEG) [16]. BCI have been shown to be very promising in numerous applications, including rehabilitation [19], human-computer interaction [5] or entertainment [12], among many other [24]. Despite this potential, most BCI applications remain prototypes that are not used in practice, outside laboratories. The main reason is the widely acknowledged low reliability and low robustness of current BCI systems, the mental task performed by the user being too often incorrectly recognised by the BCI [16]. These poor performances are due in part to the imperfect signal processing algorithms used to analyse EEG signals and recognise the user's mental state from them. Indeed, these algorithms are not yet able to extract robustly a relevant information from EEG signals despite the various noise sources, the signal non-stationarity and the limited amount of data available [24, 16]. However, this is not the only reason that may explain such poor performance and reliability. In particular, there is another component of the BCI loop that may also be deficient: the user him/herself who may not be able to produce reliable EEG patterns. Indeed, it is widely acknowledged that "BCI use is a skill" [26], which means the user must be properly trained to be able to successfully use the BCI. If the BCI user is indeed unable to correctly perform the desired mental commands, whatever the signal processing algorithms used, there would be no way to properly identify them. Despite this, the BCI community has focused the majority of its research efforts on signal processing and machine learning, mostly neglecting the human in the loop.

In this paper, we argue that the user is one of the most critical component of the BCI loop that may explain the limited reliability of current BCI. This does not mean that BCI users are bad or incompetent. This means that the way current BCI training protocols are designed is inappropriate, making BCI users unable to properly learn and use the BCI skill. Indeed, based on a careful analysis of feedback and instructional design literature, we have identified numerous flaws in the design of current BCI training appraoches. From an instructional design point of view, such flaws are known to impede successful learning and could thus explain the poor BCI performances or the fact that some people cannot use a BCI at all (the so-called BCI illiteracy [2]). In this paper, we therefore describe the flaws we have identified in the designs of BCI training approaches. Moreover, for each of these flaws, we propose new directions that are theoretically expected to solve it and thus to lead to an efficient learning of the BCI skill.

This paper is organized as follows: Next section describes how current BCI training approaches work. Then, the following section identifies the flaws in the design of these classic approaches, and propose new directions to overcome them. More precisely, these flaws and new directions are targeted at different levels of the training approaches: at the level of the feedback the user receives, at the level of the instructions provided to him/her, and finally at the level of the training tasks. The last section concludes the paper.

Current BCI training approaches

BCI control being a skill, it has to be learned, refined and mastered by the BCI user. It should be noted that in this paper we only focus on spontaneous BCI, that is BCI in which the user has to perform spontaneously a given mental task, each task being associated to a given control command. We do not consider BCI based on Evoked Potentials, such as P300-based BCI. Indeed, these latter rely on brain responses evoked by external stimulus and as such they do not require nor involve human training [26]. Neurofeedback training has been proved to be a necessary component to learn the BCI skill [17]. Neurofeedback consists in providing the user with a real-time feedback about his/her own brain activity so that he/she can learn to voluntarily control it. However, despite the claimed importance of neurofeedback training, there have been suprisingly few studies on the impact of various training approaches on BCI performances and user training. In fact, BCI training principles have been mostly the same for years, and depend mostly on the type of BCI category used [26]:

- *The operant conditioning approach*, in which the EEG signal decoder/classifier is fixed and unknown to the user, and this user has to figure out how to control a cursor by modulating his/her brain activity in a specific way. Using this kind of approach, the training can last for weeks or even months before the user can control the BCI. However, once this is done, the control achieved is generally stable and robust.

- *The machine learning approach*, in which the EEG decoder/classifier is optimized on examples of EEG signals collected from the user while he/she performs the targeted mental tasks. With this approach the training time before the user can control the BCI is much shortened (about 20 minutes). However, the performance may not be as good and stable as with operant conditioning, and a significant proportion of users (around 20%) are not able to use a BCI in this way [2]. This is the most used approach.

These two approaches differ in the way the decoder works (fixed vs optimized on EEG data) and on the instructions provided to the user (e.g., moving the cursor by modulating brain activity in a way to be identified vs performing a given mental task), but the remaining elements of the training approaches are roughly similar. First, the global objective is the same, typically moving an element on screen in different directions depending on the EEG pattern produced. The feedback provided is also similar since it is generally a simple uni-modal (generally visual) feedback indicating the mental task recognized by the decoder together with the confidence in this recognition. It is generally represented by an extending bar or a moving cursor [17] (see, e.g., Figure 1). Typically, the bar/cursor goes in the required direction if the mental task is correctly recognized and goes in the opposite direction otherwise. The speed of the bar extension or of the cursor movement is also proportional to the decoder confidence in its decision. Finally, the training protocol is also similar. Indeed, with both approaches, the user is trained following a synchronous (or system-paced) protocol, i.e., a protocol in which the user is required to do specific tasks (e.g., extending the bar towards the left by imagining left hand movements) in specific time periods only. The same protocol is usually repeated until the user has learnt the BCI skill, i.e., until he/she has achieved a given performance, usually in terms of mental state correct recognition rate.

Fundamental research on feedback and educational psychology have studied for years the properties of successful training approaches. As we will see in the following section, these BCI training approaches unfortunately have few of such properties.

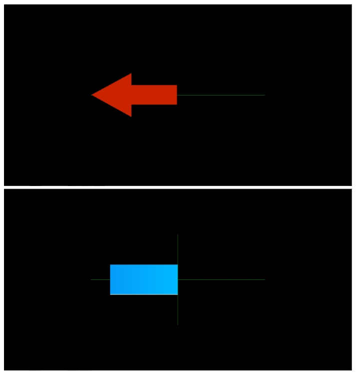

Figure 1: Example of the display of a classic BCI training protocol. Up: An arrow pointing left indicates the learner to imagine a left hand movement. Down: A feedback bar is provided to the learner. The direction and length of this bar indicate the classifier output and thus the recognized mental task. Indeed, the bar goes left for an identified imagined left hand movement, and right for an identified imagined right hand movement.

Flaws and new directions to solve them

Current BCI training approaches, as described in the previous section, have proved to be useful in the sense that they indeed enabled a number of users to learn how to voluntarily control and modulate their own brain activity. In other words, these approaches have made BCI control possible, which was a great step forward. Nevertheless, while they made BCI control possible, BCI control still has poor performances, in terms of speed or accuracy, and several people cannot use a BCI at al [2], at least using current approachs. In fact, it seems that these existing training procedures were most likely designed with little consideration for research results in the field of instructional design and educational psychology. Indeed, these research areas have identified the key elements for a successful instructional design. Unfortunately, even though BCI training approaches are instructional designs, they appear not to follow guidelines provided by these research fields. As we will see below, they are actually quite far from an ideal instructional design, which could explain the still poor performances of BCI and the high rate of illiteracy. In the following, we analyse the design of BCI training approaches at three levels: 1) at the level of the feedback, 2) at the level of the instructions provided to the user and 3) at the level of the training tasks. For each level, we identify the flaws in BCI approaches and propose new directions to make the design efficient.

Feedback

Feedback is known to be a significant factor to motivate learning [22]. Moreover, it has been shown that providing extensive feedback to a user leads to efficient and high quality learning [9]. However, this is not true for any kind of feedback, and a poorly designed feedback could actually deteriorate motivations and impede a successful learning [22].

What a good feedback should be

To be effective, “feedback should be non-evaluative, supportive, timely and specific” [22]. It should indicate the user how to improve the task [22] rather than just indicating whether the task was done correctly or not [22, 9]. It should signal a gap between current level of performance and some desired level of performance, hence reducing uncertainty for the user about how he is doing [22, 9]. In other words, Hattie describes a good feedback as a feedback that can answer the following questions: “where am I going? (what are the goals), how am I going? (progress towards the goal), where to next? (what activities need to be undertaken)” [9]. Feedback should also conduct to a feeling of competence, in order to increase motivation (whether intrinsic or extrinsic) and thus learning efficiency and efforts [21]. Finally, an ideal “feedback needs to be clear, purposeful, meaningful” [9].

What BCI feedback is

Unfortunately, BCI feedback is nearly none of this. Indeed, BCI feedback is evaluative and corrective, i.e., it continuously indicates the user whether he/she performed the task correctly. Also, It does not aim at supporting the user, being only corrective. BCI feedback also does not do anything to help the user feel competent at BCI control. More importantly, BCI is non-specific since it does not explain why or what was good or bad about the task performed by the user. With the machine learning approach, BCI feedback might also be unclear and meaningless, if it is based on a classifier trained on incorrectly performed mental tasks. Unfortunately, this situation is likely, since first time users have by definition never used a BCI before, and thus cannot be expected to perform the required mental tasks correctly from the start. In other words, for new BCI users, the feedback will indicate them they have done well if they performed the mental task as badly as they did the very first time. Naturally, this is unlikely to be meaningful.

What BCI feedback should be
To work and to be efficient, BCI feedback should therefore be 1) non-evaluative and supportive, 2) meaningful and 3) specific, i.e., explanatory. Additionnally we will show that BCI feedback could also benefit from multimodality and more engaging environments.

The need to be non-evaluative and supportive seems to encourage the use of positive feedback, i.e., feedback only provided when the user did well, to let him/her know he/she did well. Hattie indeed recommands the use of positive feedback, at least for beginners and people who want to do the task (as opposed to people who have to do it) [9]. This is also supported by two of the few studies that explored alternative feedback for BCI. These studies indeed showed that biased feedback (making the user believe he/she did better than what he/she actually did) or positive feedback works and improve performances, at least for new or inexperienced BCI users [4, 6]. Positive feedback was shown to decrease performance for advanced BCI users though. This seems in line with research results on feedback which advocate the use of disconfirmatory feedback for highly self-efficacious learners [9].

The need to provide meaningful feedback suggests that, in the machine learning approach to BCI, the classifier used should be carefully selected. In particular, if the user initially has bad performance, it may be worth not using a classifier trained on the data from this user (which are bad examples of correctly performed mental tasks). Rather, it could be worth using a subject-independent classifier [14, 7], trained on data corresponding to mental tasks correctly performed by other users. In this way, the classifier output is more likely to be a meaningful feedback, indicating (at least roughly) when the user did the task correctly. This is supported by the study of Vidaurre, who designed a training protocol able to teach some BCI users initially considered as illiterate to use a BCI [25]. Indeed, the initial stage of this protocol used generic and subject-independent features and classifier.

More importantly, BCI feedback needs to be specific and explanatory. This means that ideally, the feedback should indicate the user what he/she did well or wrong, and how to improve this. For the moment BCI feedback is only corrective, which means the user has to figure this out all by himself, without any clue. Since one cannot be aware of his own brain activity without neurofeedback, this is likely to be very difficult or even impossible for some. BCI feedback should therefore provides more information about the brain activity features used by the BCI rather than simply the classifier output (which aggregates everything together). This can be achieved in several ways:

- By providing as feedback the value of a few relevant features (e.g., the features with the largest weights in the classifier). This indeed provides a richer feedback, giving more clues to the user as to what may be going well or not. The number of features shown as feedback should be maintained small however. Indeed, an efficient feedback should not be too long and too complex, and should be provided in manageable pieces [22]. Moreover, human working memory being limited to 7 information elements at a time on average, one should show less than 7 features as feedback [23].

- By showing a global picture of relevant brain activity to the user, e.g., 2D or 3D topography of cortical activation obtained by inverse solutions [3, 11]. Thus, the user could identify by him/herself what caracterizes good and bad brain activity patterns. Moreover, one of the rare studies on BCI feedback has shown that a neurofeedback consisting of a real-time cortical map of the user brain activity increased BCI performances [11].

- By showing users a feedback actually describing the quality of the mental task he/she performed. This is not easy since so far, the quality of the mental tasks has been mostly assessed using correct recognition rates. How this recognition rate is of little help to the user. Rather, we should identify the properties of a good mental task (e.g., of a good imagined movement), e.g., in terms of strength of the Event Related Desynchronisation/Synchronisation (ERD/ERS) [20], localization, spatial spread, stability over time of this ERD/ERS, etc. Then we should feedback to the user these values. As far as we know, this has never be done but would make a BCI feedback that complies with feedback guidelines. Indeed, such a feedback would actually indicate a gap between current performances (the mental task performed by the user) and a desired level of performance (a good mental task) [22, 9]. This would also enable to focus on the user's progress, which is recommanded [22, 9], and thus help him to feel competent [21].

Current BCI feedback being mostly visual, and unimodal, it may also benefit from multimodality. Although, research on the benefits of providing learners with multiple representations have produced mixed results, a carefully designed multimodal feedback may prove useful [1]. Similarly, among the few studies that explored multimodal feedback for BCI, results have been mixed: a combination of audio and visual feedback has been shown to decrease performances [10] while a combination of haptic and visual feedback increased performances [8]. These mixed results are well summarized by Ainsworth, who mentioned that "By switching between representations learners can compensate for weaknesses in their strategy. However, if learners are attempting to relate different representations, then this may provide a source of difficulty" [1]. This work also suggests that the content of the representations may be more important than the modalities used for each representation [1]. In particular, an efficient multimodal representation should use the same formats and operators on each representation, i.e., one should be able to interpret the different representations in a similar way [1]. The different representations should also have a similar specificity, i.e., the same granularity of explanatory content [1]. Finally, there should be some redundancy between representations so that the user can easily relate them [1]. This suggests that a multimodal BCI feedback respecting these guidelines may be useful. For instance, the work in [10] used different granularity for the audio and visual modalities, the visual feedback being continuous while the audio one was discrete. This could explain while it decreased BCI performances. On the contrary, the work in [8] used the same granularity for both visual and haptic feedback, which increased BCI performances.

It should also be mentioned that high quality learning also requires authentic motivation [21]. This means the feedback should be inherently motivating for the learner and have an appeal of novelty, challenge or aesthetic value [21]. This supports the use of more engaging feedback environments rather than boring and basic feedbacks such as classic bar or cursor feedbacks. Results in using BCI with game-like or virtual reality feedback environments are in line with these recommandations, their use having been shown to increase BCI performances [12, 13].

Instructions

BCI training approaches can also be improved at the level of the instructions provided to the user before actually starting the training. Indeed, in current BCI training procedures, instructions are rarely considered, and often not even mentioned in the papers. Most of the time they simply consist in asking the subject to perform the targeted mental tasks, or to move the cursor or bar in the required direction. An important exception is the work of Neuper, who showed that specifically instructing the user to perform kinesthetic imagination of movements rather than visual imagination of movements substantially improved performances [18]. This suggests than instructions are important, which is confirmed by instructional design literature [22, 9]. Indeed, it is known that feedback is more effective when goals are clearly defined and specific [22, 9]. This stresses that when providing instructions to a user about the BCI training procedure, we should also clearly state the goals and objectives of the training. The real objective of a BCI training session is not to move a bar left or right nor to merely imagined movements. It is to help the user producing clear, specific and stable brain patterns. This goal should therefore be explicitly mentioned to the user so that he can know where to go and what is expected from him. In this way he/she will really benefit from the feedback during training to reach this goal.

Feedback itself is also an element on which instructions could be provided. Indeed, for the feedback to be efficient, the learner should understand the representations involved [1]. For the learner, this can involve learning to ignore potentially erroneous intuition that he/she may have about the meaning of the feedback. Some researchers even argue that learner should be taught how to interpret and understand the representations and thus the feedback [1]. This suggest that instructions should also be provided to the BCI users in order to explain him the meaning of the feedback. This is particularly true if the feedback is related to a classifier output, whose actual meaning (e.g., the distance to a separating hyperplane) is unlikely to be intuitive for people not familiar with classification, i.e., for most BCI users.

Tasks

The last part of BCI instructional design that can be improved is related to the tasks users have to complete. As mentioned before, BCI training tasks are mostly synchronous (a.k.a. system paced) and repeated identically until the users has learned the BCI skill. However, research on education and learning recommands to follow a different approach [1, 22, 9, 21, 23].

First, in general, training tasks should be progressive and adaptive: the learners should first manipulate the least complex representations and should then be progressively introduced to new representation as his/her expertise grows [1]. In a similar fashion, the training protocol should provide the user with challenging assignments [9], but not set too high [22]. Moreovoer, it has been shown that the use of scaffolding also enhances learning in early stage of training, but should be removed in later stages [22]. Finally, studies have revealed that student could increase their efforts if these can lead to more challenging tasks or higher quality experiences [9]. This supports that BCI training protocols and tasks should be adaptive, with a difficulty that increases as the user increases his/her skills with BCI. For instance, the user could be asked to try out a single mental task at the beginning, rather than all of them at once. Then, he/she will be asked to perform different mental tasks as he/she starts to master the initial ones. Alternatively, the user could be asked to work initially on a single property describing the quality of his/her mental tasks (see Section "Feeback"). Then he will progressively be asked to try to improve more and more of these properties until he/she reached a satisfactory quality level of mental imagery. In [15], McFarland et al have followed a similar approach by first training users to performed 1D control of a cursor, then 2D control and finally 3D control. This work was the first time 3D control of a cursor was achieved with EEG-based BCI, which again, supports the need for progressive training tasks.

Then, Ryan and Shute stressed that offering learners autonomy and the possibility to proceed at their own pace increases their motivation and makes them learn more efficiently [21, 22]. This suggest that BCI training protocols should include more free or even self-paced BCI sessions. In other words, users should be offered - at least from time to time - the possibility to decide the mental task they will perform, rather than always doing the one instructed by the program. They should be offered to do so either when instructed by the computer (synchronous BCI) or, which should be even better, whenever they want too (asynchronous/self-paced BCI).

Finally, educational research has shown that variability over training tasks and problems encourage the learners to build abstractions since it increases the probability to identify useful features and strategies and to distinguish them from irrelevant ones [1, 23]. This suggests that, in addition to be of increasing difficulty, BCI training tasks should also include variety in the tasks the users has to complete. Rather than doing exactly the same tasks over and over again, e.g., imagining the same left and right hand movements, the users should be asked to perform slightly different tasks from one trial to the next. For instance, the user would still be asked to perform imagined movements, but he/she could be asked to vary the speed of the imagined movement, its strength, the duration of the imagination, the gesture imagined, etc. This is expected to help the user identifies successful mental strategies as well as the important caracteristics of a good mental task.

Conclusion

Based on a study of educational psychology and instructional design research papers, we have highlighted that BCI training approaches were inappropriate and could benefit from multiple fundamental improvements that could increase BCI performances and reduce BCI illiteracy. We have identified the flaws of BCI training protocols and proposed new directions to solve these flaws and make BCI training efficient. In summary, we advocate to provide a BCI feedback that is 1) positive feedback in early training stage and disconfirmatory in later stages, 2) meaningful, i.e., not related to the output of a classifier trained on incorrectly performed mental tasks and 3) specific and explanatory, i.e., which provides the user more information about his/her brain activity than the classifier output. This last point could be achieved by using as feedback 1) a few relevant features, 2) a global view of brain activity such as topographies, or 3) measures of the quality of the mental tasks performed (which may be different than the classifier features). Instructions could be improved as well, by defining a clear and specific learning objective for the user and explaining it to this user. Instructions may also be provided to explain how the feedback works and should be interpreted. Finally, BCI training tasks also deserves improvement and should be 1) adaptive with increasing complexity and difficulty, 2) self-paced and 3) should include a variety of tasks. With this new study, we hope that the BCI community will realize that much still needs to be done about training procedures for BCI. This also means that BCI performances still have much potential for further improvement. We provide here a number of directions for further research, which we expect will contribute to motivate researchers to explore these areas and to further advance the field of BCI design.

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