On the need for alternative feedback training approaches for BCI

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One of the most serious issue with current BCI systems is their lack of reliability and poor performances. These poor performances are due in part to the imperfect signal processing algorithms used, which 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. However, this is most probably not the only reason that can explain such poor performance and reliability. In particular, there are several other components of the BCI loop that may also be deficient. This includes, for instance, the interaction technique used, which has to be carefully designed and improved as well, but this can also be the user himself who may not be able to produce reliable EEG patterns. If this is the case, whatever the signal processing algorithms used, there would be no way to properly identify the mental command produced by the user. 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.

We have good reasons to believe 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 feedback training protocols are designed is most probably inappropriate, making BCI users enable to properly learn and use the BCI skill. Indeed, it is widely acknowledged that "BCI use is a skill" [1], which means the user must be properly trained to be able to successfully use the BCI. An essential component of any training mechanism is the feedback, and BCI is no exception, with neurofeedback being acknowledged as a necessary component to learn the BCI skill [2]. However, despite this claimed importance, there have been suprisingly few studies on the impact of various feedback strategies on BCI performance 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:

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 the cursor by modulating his brain activity in a specific way.

The machine learning approach, in which the EEG decoder/classifier is optimized on examples of EEG signals collected from the user while he performs the targeted mental tasks. This is the most used approach.

These two approaches differ in the way the decoder works, but generally use a similar kind of feedback: an uni-modal (generally visual) feedback indicating the confidence of the decoder in the mental task recognized. It is represented, for instance, by an extending bar or a moving cursor [2]. Such feedback training approaches have been used mostly unchanged and unquestioned since their creation. In this paper, we advocate that such approaches are suboptimal, and that there is a need for alternative approaches with the potential to greatly increase BCI performances and reduce the so-called BCI illiteracy [3].

To make our point, let first consider a thought-experiment in which such BCI training approaches will be applied to the learning of a common task of everyday, such as riding a bike. Imagine someone (hereafter denoted as the student) who has never ridden a bike before and who is trained to do so using the same training principle as what is used for BCI. The bike training procedure will thus have the following properties and constraints:

1 - The student will not be shown how to ride a bike nor what a successful bike ride looks like. He will have to figure it out himself. He can be given some oral instructions about how to ride a bike though. The analogy with BCI is that subjects are not shown what a successful performance of the targeted mental tasks is. For instance, BCI subjects are not shown what a properly executed motor imagery looks like, e.g., in terms of spectral of spatial characteristics of the EEG signals. They can be provided with oral instructions though [4].

2 - The student will be enabled to see the bike while he is trying to ride it, but will not be enabled to hear (audio feedback) nor to feel (haptic information) it. The analogy with BCI is that subjects are provided with a single feedback modality (usually visual feedback).

3 - The student will only be allowed to try the bike during short and imposed periods of time. Moreover, he will have to do a specific task with the bike, and will not be allowed to explore the bike use as he may want to. The analogy with BCI is that initial BCI trainings are done in a synchronous way, in which the subject has to perform the required mental tasks in specific and short (e.g., around 5s for motor imagery) time intervals.

4 - The feedback provided to the student will only indicate him how good or bad he is globally driving the bike but not at all what is specifically good or bad nor why this is good or bad. He will have to figure it out himself. In the case of the machine learning approach, this feedback will have another property: it will indicate a good performance when the bike ride done by the student is very similar to the bike rides he did when collecting examples to calibrate the classifier. It should be reminded that these examples are collected by asking the student to ride the bike, without any feedback. Since the student has never ridden a bike before, and is not receiving any feedback, it is rather unlikely that he can ride the bike properly from the very first time. Still, the feedback he is provided with subsequently is based on those initial rides. In other words, the feedback will be positive when the student is riding the bike as incorrectly as when he tried to ride it the very first time. Otherwise the feedback will be negative. The analogy with BCI is that BCI feedback is generally only related to the classifier output, that is to the confidence in the mental tasks recognized. With the machine learning approach to BCI, this classifier is optimized on examples of EEG signals collected from the subjects performing mental tasks for the very first time.

With all these properties and constraints, the student will have most probably a lot of trouble understanding how to ride a bike. He might even not be able to learn to do so at all. Indeed, summarizing, the bike riding student is not provided with a detailed goal or objective to achieve ; is not given time to practice at his own pace ; and he is provided with a feedback that is unimodal, unspecific (i.e., it does not indicate what is good or bad nor why it is so) and which may be irrelevant (with the machine learning approach, the feedback is based on examples that are likely to be incorrectly executed).

This training protocol is therefore clearly suboptimal, and we will not be surprised if a substantial proportion of students will perform poorly at, or even cannot do bike riding after such a training. Therefore we should not be surprised if BCI users trained using such an approach would perform poorly or would not be able to use a BCI at all. This is not only common sense: this is also supported by psychology research results about education and training [5, 6]. Indeed, in these fields, it is known that to be effective, “feedback should be non-evaluative, supportive, timely and specific” [6]. In contrast, BCI feedback is evaluative (it indicates the subjects how good or bad he did), neutral (it does not aims at supporting nor depreciating the subject), regular (it is always given at the same times) and non-specific (it does not explain why or what it was good or bad). Feedback is also “of little use when there is no initial learning or surface information” [5]. BCI feedback generally cannot rely on such an initial learning, since BCI subjects are generally not told what a successful mental task is, e.g., for motor imagery, they are not told that they should produce contralateral ERD in the mu and beta bands. Finally, an ideal “feedback needs to be clear, purposeful, meaningful” [5]. With the machine learning approach, BCI feedback might be unclear and meaningless, if based on a classifier trained on incorrectly performed mental tasks (which is likely). It is generally also not purposeful, since it is not related to the goal to reach. For instance, if we want the BCI subject to be able to produce strong mu and beta ERD/ERS during motor imagery, the feedback should show these mu and beta ERD/ERS to the subject. This is rarely the case. All these results also support that BCI feedback and training approaches are sub-optimal. There have been surprisingly little research about feedback training for BCI, and the rare exceptions also support that this could be much improved. Indeed, it has been shown that positive or biaised feedback [7], self-paced specific feedback training using inverse solutions [8], multimodal feedback [9] and adaptive feedback [10] could all improve BCI performances. This further illustrates that there is a strong need for alternative feedback training approaches for BCI, and that these have the potential to greatly improve BCI performances and reduce BCI illiteracy, maybe more than signal processing methods alone.

References

[1] J.R. Wolpaw et al. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6):767–791, 2002.

[2] C. Neuper and G. Pfurtscheller. *Brain-Computer Interfaces*, chapter Neurofeedback Training for BCI Control, pages 65–78. The Frontiers Collection, 2010.

[3] B.Z. Allison and C. Neuper. Could anyone use a BCI? In Desney S. Tan and Anton Nijholt, editors, *Brain-Computer Interfaces*, volume 0 of *Human-Computer Interaction Series*, pages 35–54. Springer London, 2010.

[4] C. Neuper et al. Imagery of motor actions: differential effects of kinesthetic and visual-motor mode of imagery in single-trial EEG. *Brain Res Cogn Brain Res.*, (3), 2005.

[5] J Hattie and H Timperley. The power of feedback. *Review of Educational Research*, 77:81–112, 2007.

[6] V.J. Shute. Focus on formative feedback. *Review of Educational Research*, 78:153–189, 2008.

[7] A. Barbero-Jimenez and M Grosse-Wentrup. Biased feedback in brain-computer interfaces. *J NeuroEng Rehab*, 7(34):1–4, 2010.

[8] H.-J. Hwang, K. Kwon, and C.-H. Im. Neurofeedback-based motor imagery training for brain-computer interface (bci). *J Neuroscience Meth*, 179(1):150 – 156, 2009.

[9] M. Gomez Rodriguez et al. Closing the sensorimotor loop: haptic feedback helps decoding of motor imagery. *J Neural Eng*, 2011.

[10] C. Vidaurre and B. Blankertz. Towards a cure for BCI illiteracy. *Brain Topography*, 23:194–198, 2010.