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How Well Can We Learn With Standard BCI Training Approaches? A Pilot Study.

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Abstract

While being very promising, brain-computer interfaces (BCI) remain barely used outside laboratories because they are not reliable enough. It has been suggested that current training approaches may be partly responsible for the poor reliability of BCIs as they do not satisfy recommendations from psychology and are thus inadequate [3]. To determine to which extent such BCI training approaches (i.e., feedback and training tasks) are suitable to learn a skill, we used them in another context (without a BCI) to train 20 users to perform simple motor tasks. While such approaches enabled learning for most subjects, results also showed that 15% of them were unable to learn these simple motor tasks, which is close to the BCI illiteracy rate [1]. This further suggests that current BCI training approaches may be an important factor of illiteracy, thus deserving more attention.

1 Introduction

Brain-computer interfaces (BCIs) are communication systems allowing users to interact with the environment, using only their brain activity [6]. BCIs, although very promising, remain barely used outside laboratories because they are not reliable enough [6]. Two main reasons have been identified. The first one, extensively investigated, concerns brain signal processing, with current classification algorithms being still imperfect [1]. The second one concerns the users themselves. Indeed, many users seem unable to acquire good BCI skills (i.e. the capacity to generate specific and stable brain activity patterns): around 20% cannot control a BCI at all (the so-called "BCI illiteracy"), while most of the remaining 80% have relatively modest performances [1]. An appropriate training is needed to acquire these skills, especially for Mental Imagery-based BCI (MI-BCI). It has been suggested that currently used training and feedback protocols, which do not take into account recommendations from psychology to optimise human learning, might be partly responsible for BCI illiteracy and poor user performance [3]. For instance, it has been shown that, for efficient learning, training protocols have to fit the user learning style and propose an increasing and adaptive difficulty [3]. Yet standard BCI training protocols are the same for all users [3]. While instructive, these studies only provide theoretical considerations about training approaches. It is therefore necessary to concretely assess whether training approaches used in BCI are appropriate to train a skill. Moreover, it is necessary to perform this evaluation independently of BCI, to rule out possible biases due to BCI complexity, non-stationarity and poor signal-to-noise ratio. Thus in this work, we propose to study these BCI training approaches without using a BCI: participants were asked to learn specific and simple motor tasks using the same feedback and training tasks used for MI-BCI. We then studied how well they could learn such motor tasks to assess the quality of the training approaches, independently of BCI use. We studied here two different approaches: 1) the training approach

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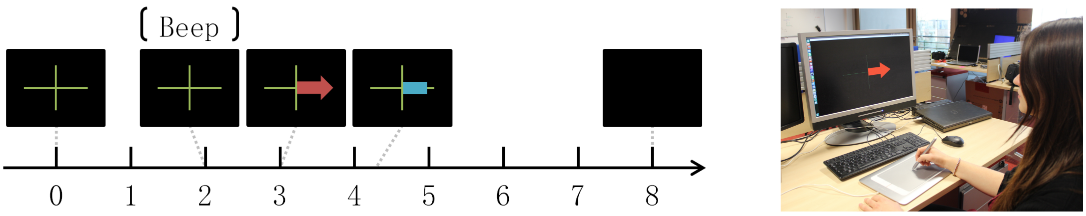
used in "standard" MI-BCI [5] and 2) a variant of it which provides some autonomy to the user. Indeed, with the "standard" approach, no autonomy is given to the user, who always has to perform the tasks required by the protocol. Yet, autonomy is known to increase motivation and learning efficiency in general [3]. Interestingly enough, the study described in [4] obtained promising results when providing more autonomy to a single BCI user.

2 Methods

Participants were asked to learn to perform two motor tasks: drawing triangles and circles with a pen on a graphic tablet (see Figure 1(b)), using standard MI-BCI training approaches [5]. Indeed, as with MI-BCI, in which users have to learn a suitable movement imagination strategy, the participants here had to learn the strategy which allows the computer to correctly recognise their drawing, e.g., they had to identify the suitable shape size, angles or speed of drawing.



(a) An 8 second-long trial

(b) Experimental Setup

Figure 1: (a) Outline of a trial from a standard run; (b) Experimental setup.

2.1 Experimental protocol

Participants had to learn to draw circles and triangles that can be recognised by the computer during different runs, which were either standard (s) or self-paced (sp). S-runs were composed of 20 trials per task. As shown in Figure 1(a)), at the beginning of each trial a green cross was displayed. After 2s, an auditory cue (a beep) announced the beginning of the task. Then, after 3s, a red arrow was displayed, indicating which task the participant had to perform: continuously drawing circles or triangles upon appearance of a left or right arrow, respectively. After 4.25s, a blue feedback bar appeared and was updated continuously for 4s. Its direction indicated the shape recognized by the classifier (left: circle, right: triangle) and its length was proportional to the classifier output (i.e., the distance to the classifier separating hyperplane), as with MI-BCI. During sp-runs, no instructions were given: the participants were asked to do the motor tasks in an autonomous and free way. Half of the participants were asked to learn using a Standard (S) training approach: they did 4 seven-minute-long s-runs. The other half learned using a training approach with increased autonomy, denoted Partially Self-Paced (PSP) approach: the 1^{st} and 4^{th} runs were s-runs, while the 2^{nd} run was replaced by a 3.5 minute long sp-run followed by a shortened s-run (10 trials per task, 3.5 minutes), and the $3rd$ run was replaced by a shortened s-run followed by a 3.5 minute long sp-run. The training duration was the same in both conditions. We studied the impact of the condition, S vs. PSP, on the recognition accuracy of triangles and circles over runs (i.e., learning effects) and on subjective experience (using a questionnaire). 20 participants (10 per group) took part in our experiment.

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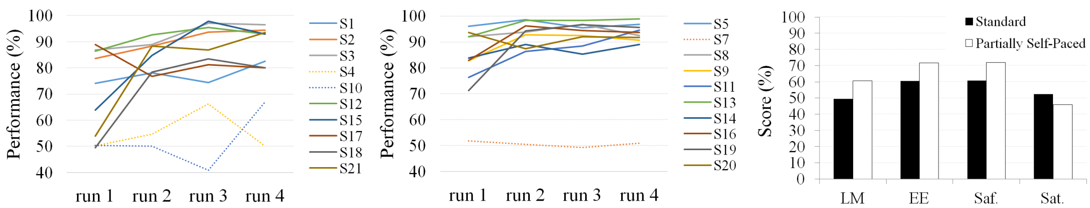
2.2 Signal Processing

In order to discriminate triangle from circle pen gestures, we used a pattern recognition approach as in BCI. From the past 1s-long time window (in a sliding window scheme, 937.5ms overlap) of the 2D pen position (16Hz sampling rate), a histogram of angles was computed. More precisely, the angles between each consecutive segment of the time window were first computed. Then the number of angles falling in the ranges 0-30^o, 30-75^o, 75-105^o, 105-150^o and 150-180^o were counted, and these 5 count values were used as input features for a Linear Discriminant Analysis (LDA) classifier. The (subject-independent) LDA classifier was trained on 60 trials from each gesture, from 2 persons (1 left-handed, 1 right-handed). The resulting classifier could discriminate triangles from circles with 73.8% classification accuracy (10-fold cross-validation on the training set), which is an accuracy equivalent to the average accuracy of a MI-BCI [2]. Classification accuracy was measured as the average number of 1s-long time windows correctly classified during the feedback period from each trial (see Figure 1(a)).

2.3 Analyses

In order to analyse the interaction between the "Condition" (2 modalities: S and PSP; independent measures) and the performance obtained at each "Run" (4 modalities: run1, run2, run3 and run4; repeated measures), we performed a 2-way ANOVA. Morevoer, we asked the participants to complete a Usability Questionnaire (UQ) which measured 4 dimensions: learnability/memorability (LM), efficiency/effectiveness (EE), safety (Saf.) and satisfaction (Sat.). Thus, we did a two-way ANOVA to analyse the interaction between the "Condition" and the "Evaluated Dimension" (4 modalities: LM, EE, saf. and sat.; repeated measures).

3 Results & Discussion



(a) "Standard" Condition (b) "Partially Self-Paced" Condition (c) Questionnaire

Figure 2: (a) (a) Performance (pen gesture classification accuracy) over runs in the S Condition; (b) Performance over runs in the PSP Condition; (c) Average UQ scores.

Irrespectively of the condition, classification accuracy results (see Figures 2(a) and 2(b)) showed that 17 out of 20 participants managed to learn the task (best run accuracy $\geq$ 82.6%), with accuracies increasing with the number of runs on average, as can be observed in BCI. However, 3 participants did not manage to learn the tasks (best run accuracy $<$ 70%). This is particularly interesting considering the simplicity of the motor tasks which ensured the users could technically perform them. Such training approaches thus seem suboptimal. Moreover, this rate of 15% of people who did not manage to learn is close to the BCI-illiteracy rate (20% [1]). Overall, this suggests that BCI illiteracy may not be due to the user only, but also substantially to the training protocol. Then, results showed neither a main effect of the

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Condition [F(1,18)=2.33; p=0.15] nor a Condition X Run interaction [F(3,45)=1.35;p=0.27] when considering all the participants. However, when the 3 illiterates are excluded, the 2-way ANOVA showed a main effect of the Condition [F(1,15)=7.48;p=0.01]: the PSP group seemed to perform better than the S group (meanPSP=91.00 $\pm$ 3.82, meanS=83.29 $\pm$ 6.95). However, random sampling of the participants led by chance to a PSP group with classification accuracies for the first run that are higher than that of the S group, which prevents us from drawing any relevant conclusion on comparative learning effects.

UQ results (see Figure 2(c)) showed no main effect of the Condition [F(1,18)=0.98; p=0.33]. However, they showed a trend towards a Condition X Evaluated Dimension interaction [F(3,54)=2.40; p=0.077], which is due to the better evaluation of LM, EE and Saf. in the PSP condition than in the S condition, which is not the case for the Sat. dimension. These results suggested that while the PSP approach is not more pleasant to learn with than the S approach, it is easier. Interestingly enough, 8 subjects reported in an open-question of the questionnaire that the feedback was very uninformative, which made learning the tasks difficult.

4 Conclusion

This study aimed to concretely assess how well one could learn a given skill with BCI training approaches. To do so, we proposed to study BCI training approaches without using BCI, i.e., we used feedback and training tasks from MI-BCI to train participants to draw triangles and circles (i.e., simple motor tasks) so these can be recognized by the computer. Half of the participants did so using a S training approach while the other half used a PSP one. In terms of learning effects, results unfortunately showed no relevant differences between conditions (S vs. PSP), due to initial performances that differed between conditions, by chance. However, irrespectively of the condition, 15% of the participants (3 out of 20) seemed unable to learn the motor tasks, despite their simplicity. This suggests that such training approaches are not optimal for learning and thus that they may be an important factor of BCI illiteracy. Concerning user experience, UQ showed a tendancy towards a better feeling of learnability/memorability, efficiency/effectiveness and safety with the PSP than with the S approach, while the satisfaction appeared similar for both. Overall, this study confirmed in practice the theoretical analyses from [3] suggesting that current BCI training approaches were suboptimal and need to be changed. In the future, we will increase the number of participants, explore the PSP approach with actual BCIs, and propose new training approaches that consider the user's cognitive style and motivational states to improve both the learning experience and performance.

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