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PERFORMANCE, TRANSFER LEARNING AND UNDERLYING PHYSIOLOGY IN CHILDREN PLAYING P300 BCI GAMES

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ABSTRACT: P300-based BCI are widely explored for item selection but few studies have examined if this interface can be used by children... The aim of the current study was to evaluate the performance of healthy children playing three different calibration-free P300 BCI games. 19 children played all three games in a random order. EEG-based online selection relied on template signals derived from a previously acquired database. All children performed the task significantly well even though all children underwent an inevitable drop of performance when comparing offline (individual) with online (template based) accuracies. Offline analyses revealed no difference in performance between games. Transfer learning from one game to the others proved possible although one game appeared slightly less generalizable. Finally, offline ERP analyses revealed differences in the early (visual) components, which we relate to each game graphical specificity. In contrast, all games did involve a strong contribution of the P300 component, which is essential to support high attention-based control.

INTRODUCTION

The most well-known P300 BCI is the so-called P300-speller which allows the user to spell words without using the peripheral nervous and muscular pathways. This interface has been developed for people with very severe neuromuscular disorders, in the aim of enabling them to communicate [1]. A good control of this interface is partly based on the subject's ability to elicit well distinguishable brain signals after a target and after a non-target stimulus, respectively. Discriminating between those two classes highly depends upon the voluntary engagement of the subject in this selective attention task [2]. A way to enhance the motivation is to provide a more playful environment. With this in mind, P300-based BCI games have been developed [3]. Moreover, it seems also possible to increase the amplitude of the P300 with training, both in the auditory [4] and visual domains [5]. Although these trainings were short and have involved very few participants, an improvement over practice was reported which was concomitant with an increase in the P300 amplitude. With the aim of setting up a BCI-based training for children with ADHD [6] we decided to develop new P300-based games to increase the diversity of the games on offer. To propose various games could be essential to keep up the motivation over long training periods, and to avoid as much as possible the drop out of participants. Another particularity of our training is that children do not control the BCI based on their own calibration signal. Indeed, ADHD children having a diminished P300 compared to controls [7], the brain response of targets and non-targets might not be distinguishable and thus the subsequent classification might not be accurate. The whole purpose of the training is to restore a proper P300 signal in those children. Therefore, we decided to build a template of the expected electrophysiological responses in healthy children and use it as the target electrophysiological response for the training of children with ADHD [6]. We used covariance matrices as features and Riemannian geometry for subsequent online classification [8]. Such an approach has shown very good results for both classification and generalization [9]. The template was built from data of a previous study were children played with a P300-based connect 4 (Fig. 1) [6]. The aim of the present study was first to evaluate the classification accuracy with 3 new games and to assess whether the difference in game configuration would induce differences in electrophysiological responses. Finally, we wanted to evaluate the robustness of transfer learning between games, and between subjects.

MATERIALS AND METHODS

Template construction

The template was built on data from a previous experiment conducted in 34 healthy children. They had to control a Connect 4 game (Fig. 1a). After a short calibration, each child played for about 80 trials. The data from 5 children were finally discarded because of technical problems or too low performance. We thus ended up building template signals on data from 29

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children (6-16 years old; 14 girls). It consists in two covariance matrices, one for the target and one for the non-target class. Precisely, the prototype ERP response is obtained by averaging the single trial responses from the target class. Then each single target trial is concatenated with this prototype ERP to create so-called super trials. These super trials are used to build covariance matrices thanks to the Sample Covariance Matrix estimator. These matrices are then averaged using the Riemannian mean to obtain the typical target covariance matrix. The same procedure applies to obtain the typical non-target covariance matrix [9].

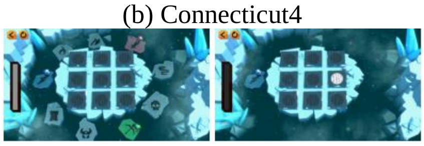
Experimental setup: 19 healthy children (6-16 years old; 11 girls) took part in this new experiment. Children had never used a BCI before and reported normal or corrected-to-normal vision. The study was approved by the ethics committee n°2016-013B. EEG signals were recorded from 16 channels using an active EEG electrode system and a Vamp amplifier (Brain Products, Germany). EEG channel locations were Fz, Cz, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, PO9, O1, Oz, O2 and PO10 following the international 10-20 system.

Experimental procedure: The 3 games have been designed and implemented by Black Sheep Studio[1] using Unity 3D [10]. The first one, Connecticut4 (C4) (Fig. 1b) is a connect 4 game, whose aim is to align 4 pawns before the computer does. For the second game, IceMemory (IM) (Fig. 1c), the aim is to memorize and find cards to make one's own character move and grab the opponents. The third game named Armageddon (AR) (Fig. 1d), is a strategic game where the goal is to protect an island from asteroids. In each game, each possible target (7 in C4, 9 in IM and AR) was visually intensified 6 times in random order before a decision was made. Both the flash duration and the interstimulus interval (ISI) were set to 100ms. Children were instructed to focus their (overt) attention onto the target and count the number of times it was flashed. To ensure that the children did not suffer from attentional disorder, parents filled-up the ADHD rating scale. One child has been removed from the analyses because of a high inattention score. We used an eye-tracker (ET, SMI REDn scientific 60Hz) to know about the targets chosen by the children. After a short calibration of the ET, children could start playing directly, thanks to the above-described template. Each child played all three games (about 20 trials each). We counterbalanced the order of the games over children.

Online processing: EEG data were processed in real-time within a home designed pipeline coded in Python among which Pyacq (https://github.com/pyacq/pyacq). Data were sampled and bandpass filtered between 1 and 20Hz. After each flash, the epoched signal (0-600ms) was concatenated with the prototype ERP response (see

(a) Connect 4 from the previous study

(b) Connecticut4



(c) IceMemory

(d) Armageddon

Figure 1: Screenshots of the BCI games, in the absence of flashes (left panel) and during one flash (right panel).

template construction section) to build a covariance matrix. Using the Riemannian distance, this covariance matrix was then compared to the target and non-target covariance matrices, respectively. We then used as a feature for (probabilistic) classification, the log ratio between those two distances. The result of this online processing was sent to the BCI-game by TCP using a ZeroMQ socket [11]. The true target location was given by analyzing the eye-tracking measures. Therefore, seven or nine zones, depending on the game, were defined on the screen, corresponding to the seven or nine potential targets. At each trial we obtained a vector of seven or nine values, providing to amount of time the child had spent looking at each zone. We considered as the target, the area that was looked at the most.

Electrophysiological offline analyses: The EEG data were finely analyzed offline, with the MNE software package [12]. EEG data were filtered between 1 and 20Hz. Then the signal was segmented into epochs of 800ms (-200ms to 600ms peri-stimuli time) and a baseline correction was applied. Epochs with an EEG signal above 150 µV or below -150 µV were marked as artifactual and discarded. To identify spatio-temporal differences between target and non-target epochs, a cluster-based permutation test was performed at the group level. Then for each spatio-temporal significant cluster we computed the averaged amplitude of the signal, for each game (C4, IM, AR) and each class (Target and Non-Target). We constructed a linear model of the averaged amplitude as a function of Games and Classes. The between subject variability limits the comparison and means that data cannot simply be pooled for analysis. Using a linear mixed-effect model (lme4 package, Linear Mixed Effects version 4) [13] is the best

[1] Black Sheep Studio is an SME located in Paris, France specialized in video games (blacksheep-studio.com).

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way to deal with such datasets, as they allow for correction of systematic variability. We accounted for the heterogeneity of accuracy values across subjects by defining them as effects with a random intercept, thus instructing the model to correct for any systematic differences between subjects (interindividual variability). We used a binomial distribution to describe the model errors.
We then analyzed the influence of two possible fixed effects onto signal amplitude:
(i) the Game effect (three levels) (ii) the Class effect (two levels). We ran a type II analysis of variance. Wald chi-square tests were used for fixed effects in linear mixed-effect models. For post-hoc tests we used the Lsmean package (Lsmean version 2.20-23) [14] where effects were considered as significant when p<0.05 and adjusted for multiple comparisons (Tukey method). All statistical analyses were performed using the R Statistical Software.

Self versus template accuracy: To evaluate the efficacy of the template, we compared in each child, the self-accuracy with the template-based one. The latter corresponds to the actual online accuracy experienced by the children.
Self accuracy refers to a (theoretical) offline measured performance that is only based on the user data. We computed it following a cross-validation procedure. Therefore, we splitted each child's data into a training set (75% of the data) and a testing set (the remaining 25%). This random split was repeated 500 times to compute an estimate of what we refer to as self accuracy. This measure was used for comparison with the template accuracy.
It was also used for comparing performance over games using a linear model of self accuracy as a function of games. Finally, we also evaluated the self accuracy within games, following the same computational procedure as above, but considering each of the three games independently.
Computing the self accuracy this way does not allow us to take in account a potential effect of time. To evaluate such a possible additional effect, we used the data of the first game presented to the children as the training set and tested the performance on the subsequent two games. We compared the generalization performance to the second and third game using a two-sided t.test.

Transfer between games: In order to evaluate the transfer between games, we computed the target and non-target covariance matrices with the signal of one game and performed the classification on the two other games We then constructed a linear model of the accuracy as a function of the game used for training. For post hoc tests we used the Lsmean package where P-values were considered as significant at P<0.05 and adjusted for the number of comparisons (Tukey method).

Relating gaze fixation and BCI accuracy: To have a more precise measure of the gaze fixation we computed a gaze fixation index G as follows:

$$G = 1 - \frac{Sobs}{Smax}$$

where Sobs is the Shannon entropy of the actual gaze orientation over possible location and Smax is the theoretical maximum entropy used for normalization (it corresponds the case where the child would have looked at all targets for the same amount of time. A G close to 1 means a very good gaze fixation on the target. Conversely, a G close to 0 corresponds to a trial where children had a poor fixation performance. For each child, we averaged this index over all trials. We then computed the Pearson correlation coefficient between G and self-accuracy, over subjects.

Good and poor performers: Relating G and self-accuracy revealed two sub-groups, one of good performers and one of poor performers. We thus decided to test the difference between targets and non-targets signals for those two groups separately. We constructed a linear model for each cluster and each game of the average signal amplitude as a function of Classes and Performance (good vs. poor performers).
We then analyzed the influence of two possible fixed effects on signal amplitude as in the section: Electrophysiological offline analyses.

RESULTS

Electrophysiological analyses: Over all games and subjects, the cluster-based permutation test revealed 4 significant clusters showing differences between targets and non-targets. The first cluster corresponded to the P100 component in occipitals areas (Time: 67-98ms; sensors: O1 and O2). The second one corresponded to the left hemisphere N200 (Time: 160-229ms; sensors: CP5, P7 and P3) and the third one to the right hemisphere N200 (Time: 194-204; sensor: CP6). These two clusters have been combined into one, named further the N200 cluster (Time: 194-204ms; sensors: CP5, P7, P3 and CP6). The last cluster corresponded to the P300 component (Time: 244-481ms; sensors: CP5, CP6, P7, P3, P4, P8, O1 and O2) (Fig. 2).

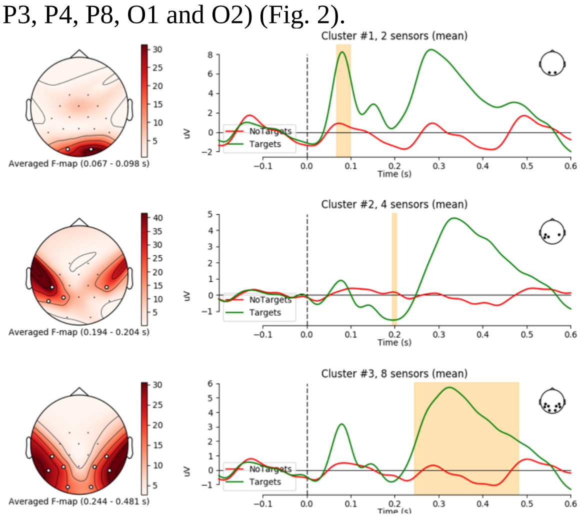

Figure 2: Spatio-temporal clusters differentiating the target and the non-target responses over all three games.

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For each of the 3 above clusters, each game and each class, we computed the mean amplitude of the ERP. For the P100, the 3*2 repeated ANOVA (game*class) revealed a main effect of class ($p < 0.001$) and a significant interaction. For both the N200 and P300, the ANOVAs revealed a main effect of the class only (Fig. 3).

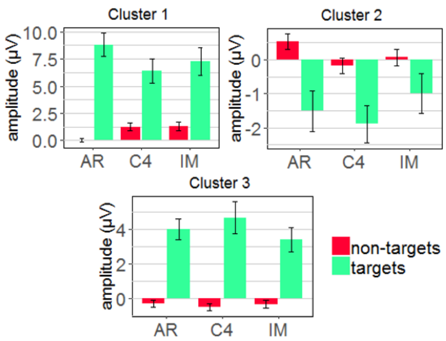

Figure 3: Averaged amplitude of the ERP for the targets and the non-targets on each cluster and for each game. There is a main effect of the class for each cluster and a significant interaction games*classes for the cluster 1. Error bars indicate S.E.M.

Evaluation of the games: Whether the learning was computed on all games or a single game only, the repeated measure ANOVAs showed no significant difference between the game classification accuracies. We found no difference between the accuracy computed on all games and the ones computed on each game independently (learning on all the games: mean = 84.79%; S.E.M = 1.82; learning on one game: mean = 86.45; S.E.M = 1.8). For subsequent analyses we thus considered the self-accuracy computed on all games only. Finally, we found no effect of time as we found no significant difference between the two classification accuracies when learning on the 1st game data (generalization to 2nd game: mean = 67.00%, S.E.M. = 5.34; generalization to 3rd game: mean = 70.33, S.E.M. = 4.90).

Transfer between games: To evaluate whether transfer is possible between games, we computed accuracies where the learning was based on trials from one game and the testing was performed on all trials from the other two games. The ANOVA showed a significant effect game used for learning. Post hoc analyses revealed higher accuracy when the learning was based on IM and AR trials compared to when it was based on C4 ones. Besides, we found a significant decrease of theses accuracy ($p < 0.001$) compared to self-accuracy.

Template evaluation: To test the possibility of using directly the template to control the games and thus get rid of the calibration, we compared the self-accuracy computed offline to the template-based accuracy. The t-test showed a significant decrease of accuracy when the children played with the template (mean = 0.55; S.E.M = 0.05). At the individual level, all children obtained a lower accuracy when playing with the template compared to self-accuracy. However, we observed a significant correlation between self-accuracy and template-based accuracy (cor = 0.62; $p = 0.006$). The more the children succeed in controlling the games (as measured by self-accuracy), the higher their performance calculated based on the template. When they played with the template all children but one performed above chance level. The comparison between the 3 games showed no significant difference between games.

Correlation between gaze fixation and BCI accuracy
There was a significant correlation between the gaze fixation index and the self-accuracy (cor = 0.77; $p < 0.001$). Hence BCI accuracy increased with the gaze fixation. This correlation also revealed two groups, one of 11 children referred to as good performers, with accuracy above 85% and a gaze fixation index above 0.90; and a second of 7 children referred to as poor performers, with an accuracy below 85% and a gaze fixation index below 0.90 (Fig. 4).

Good vs. Poor performers: For the P100, the 2*2 repeated measure ANOVA (good/poor performers * classes) we obtained a main effect of class and no effect between good and poor performers for all games. For the N200, we obtained a main effect of class for C4 and a trend for IM ($p = 0.061$). For AR, the interaction proved significant and was driven by the target class: the N200 amplitude was

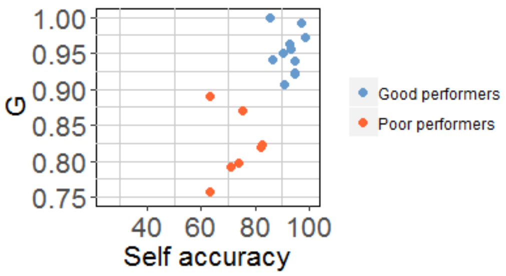

Figure 4: Correlation between the self accuracy and the gaze fixation index (cor = 0.77; $p < 0.001$)

higher for good performers ($p = 0.047$). Finally, for the P300, we obtained a main effect of class for all three games, a main effect of group for IM and an interaction effect for C4 and IM, with a significantly higher amplitude in good performers compared to poor performers for class target (C4: $p = 0.05$; IM: $p = 0.005$) (Fig. 5).

DISCUSSION

This study had two main aims, first to evaluate the 3 new P300-based BCI games and then to test the transfer or generalizability between games. As shown in Fig. 1, stimulation configurations differ between games. In C4, a stimulus corresponds to the flash on one column, so it covers the full height of the screen. In IM the flashes are much smaller and grouped in the center of the screen. On the contrary, in AR the flashes are bigger and cover the

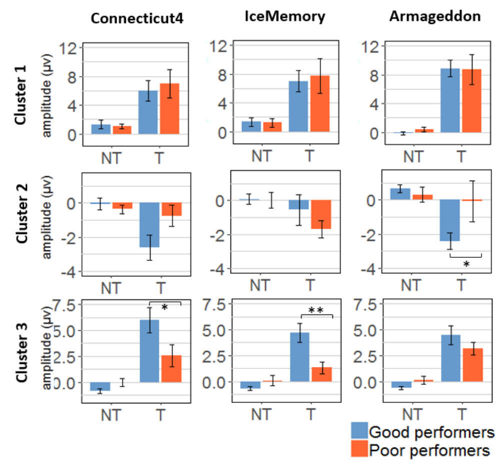

Figure 5: Averaged amplitude of the ERP for target and non-target, in each cluster and for good (blue) and poor (red) performers, respectively. We found a significant difference between good and poor performers for class target in C4 and IM, in the P300 cluster; and for AR in the N200 cluster. Error bars indicate S.E.M.

whole screen altogether. These differences between the flash configurations may induce differences in the ERPs. The ERPs corresponding to the average over target trials from all games, revealed the three components: early visual potential P100; the N200 and the P300 [15], [16]. To evaluate the implication of these three ERP components in differentiating target and non-target stimuli, we compared them for the three games, respectively. The significant difference between targets and non-targets for the three clusters suggests that the three components participate to the classification in all three games. The interaction between games and classes for the first cluster suggests that even if all the games elicited a P100, its relative contribution varies between games. In AR, the non-targets do not elicit a P100 at all, contrary to targets that elicit a high P100. In C4 and IM, the non-targets elicit a small P100 and the difference between targets and non-targets is less pronounced. Visual early potentials (P100 and N200) are larger when the stimulus is foveated [17], which may explain the larger influence of the P100 in AR, where stimuli are large and more far away from each other. Because of this configuration, it is easier for the subject to look at one flash only and to ignore the other (distracting) ones. This explains the absence of P100 for non-targets stimuli in AR. In other games, as the flashes are more grouped, it is more difficult to ignore the non-relevant flashes, that do yield a small P100.

In contrast, the fact that we observe a large P300 component in response to target stimuli, regardless of the game, indicates that the ability to selectively fixate the target is not affected by stimulus size and configuration. Indeed, we did not find any difference in self accuracy between games. A result in BCI performance that is in line with the ERP findings.

We then tested if transfer learning is possible between games. We found a significant difference in performance when learning from C4 trials compared to when learning for the other two game data. C4 appears less generalizable. Reasons for that are not obvious given the ERP findings. However, one should not forget that the ERP clusters do not exactly match the BCI features used online. Covariance matrices are built with the signal of all electrodes and a large time window, while the clusters are spatially and temporally more limited. Including all the electrodes, the design of C4 might induce covariance matrices more distant to the covariance matrices of the other games. When children played based on the template, which was the case online, we obtain a lower accuracy compared to the self-accuracy computed offline following a cross-validation procedure. However, despite this inevitable loss of accuracy when relying on template signals obtained in other children and BCI conditions [18], [19], all children but one performed above chance level online. Many studies have tried to reduce the calibration time without impacting the classification performance. One possibility is to use a subject dependent approach. It consists in using only a few epochs of each class from the subject, to tunes a template built on other subjects. Adding a small amount of data from the new subject seems to be sufficient to compensate for the inter-subjects variability [9]. An approach that could prove useful in this context too, in the near future.

Interestingly, the positive correlation between self-accuracy and template-based accuracy suggest that good performer behave alike, which fits perfectly with our objective to establish a template for the training of ADHD children in order to teach them how to produce a typical P300, which would be the hallmark of the ability to deploy sustained, spatial selective attention.

We also observed a positive correlation between stability in gaze fixation and BCI accuracy. It seems obvious that focusing gaze on the target concurs to focusing attention onto that target. Conversely, a lower gaze fixation index could indicate that children have been distracted by the non-target flashes and made saccade towards them, hence yielding BCI selection errors and a lower accuracy. This correlation also allowed to dissociate two groups: good performers (n = 11) showing a good classification accuracy and a good gaze fixation, and poor performers (n = 7) showing the reverse pattern. This allowed us to compare them in terms ERPs which revealed no difference in early visual potentials (P100) but mostly a difference in the P300 and N200 in a lesser extent. This suggest that although gaze fixation was high overall, including in poor performers (as testified by a large difference in P100), slight instability in gaze fixation is accompanied by some instability in attentional focus and has a dramatic effect on later, attention related, components, especially the P300. Although less reported in this context, the N200 is known to underline both processes of gaze fixation and attention to the target [20]. Altogether, these results emphasize that gaze orientation is mandatory for good BCI performance, but not sufficient as the most important ERP components are the ones related to (covert) sustained attention. A finding that supports the idea that P300 based BCI training could be efficient in ADHD children.

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CONCLUSION

We conclude that it is possible to use this kind of template to play BCI P300 games without calibration. There is an obvious drop of performance compared to an individual calibration, but the use of this kind of template may prove sufficient in the context of training. We found no difference in classification accuracies between games but differences in game design yielded differences at the physiological level. This should be further investigated in the future in order to optimize the training, for instance by presenting the games in a specific order. Theses results could also allow to guide the design of new games to target specific components, toward a more individualized approach.

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