Cross monitoring and workload detection in a cooperative environment

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Cooperation and especially cross monitoring are critical in the cockpit notably under high workload and stressful conditions. Studying those behaviors and their associated mental states is crucial to understand team errors that can lead to incidents or accidents. Assessing those mental states objectively could allow designing a better training and potentially a better cockpit interface.

Hence, we asked 20 participants (10 couples) to take part in an experiment that included a modified version of the MATB micro-world. EEG was recorded with a BioSemi 64 electrodes for each participant. Each couple performed 8 scenarios of 5mn each. Two levels of difficulty were modulated separately for each participant (Easy vs Hard). They were also asked either to cross-monitor and help their partner or not (control condition), resulting in a total of 8 possible conditions.

A classifier was used to detect if we could discriminate those levels of workload for each participant and moreover if we could discriminate the cross-monitoring vs the control condition. To do so the classifier was trained with frequency features (theta to low beta) from 2-sec epochs coming from each scenario. Each epoch was preprocessed independently with the Artifact Reconstruction Subspace algorithm.

A subject-dependent 8-class shrinkage LDA was used with a One-Versus-The-Rest (OVR) strategy, with a 5-Fold cross-validation procedure. For an 8 class problem the theoretical threshold is 12.5%, interestingly an average of 44 % for the Pilot Flying and 42% for the pilot monitoring was reached. This study demonstrates that cross- monitoring and more generally cooperative behavior can be detected by EEG although more participants and more complementary analyses should be done.

Keywords: Neuroergonomics, Artifact Subspace Reconstruction (ASR); Classification; Cooperation; Workload; EEG; Cross-Monitoring; MATBII

Looking for neurophysiological correlates of brain-computer interface learning

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Non-invasive Brain-Computer Interfaces (BCIs) can exploit the ability of subjects to voluntary modulate their brain activity through mental imagery. Despite its clinical applications [1]-[2], controlling a BCI appears to require a skill acquisition that can last several weeks to reach relatively high-performance in control, without being sufficient for 15 to 30 % of the users [3], [4]. This gap has motivated a deeper understanding of mechanisms associated with motor imagery (MI) tasks [5]–[8].

Twenty BCI-naive subjects (aged 27.45 ± 4.01 years, 12 men) participated to four BCI sessions each. Power spectra and imaginary coherence between each pair of region of interest in the source space were used to study respectively, the evolution of the activations and of the functional connectivity during the training from electroencephalographic signals.

We found a progressive involvement of distributed sources in the cortical hemisphere contralateral to the movement corresponding to a significant power decrease ($p < 0.025$) within both a and b ranges that tended to focus more on the pre-and postcentral gyri at the end of the training. A progressive decrease of task-related connectivity in both a and b ranges across sessions was also observed. Power changes in a and b ranges significantly predicted the BCI accuracy in the next session ($p < 0.005$ in a2). The connectivity decrease in the frontal and the temporal areas was associated with a better future performance in a2.

We elicited cortical changes associated with a dynamic brain reorganization during BCI training. These changes were characterized by an increase of the desynchronization rate and by a decrease of the connectivity that can be used as predictors of BCI performance. Taken together, our results offer insights into processes underlying BCI training.

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Transfer Learning between BCI datasets with different dimensions

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It is standard practice to consider that two BCI datasets recorded with different numbers of electrodes are not compatible between each other. This imposes substantial limitations for Transfer Learning applications, since it confines its use to data coming only from subjects in the same database. In this work, we propose a method that allows using data from a source dataset registered on m electrodes to classify data points of a target dataset with n electrodes (without loss of generality, we will consider that $m > n$).

Our proposal relies on the Riemannian geometry framework applied to BCI [1], where one uses spatial covariance matrices as statistical descriptors for EEG epochs. The data points from the source dataset live in $R^{m \times m}$ and those from the target dataset are in $R^{n \times n}$. The method consists of two steps. Firstly, we construct an isometric transformation T that maps points from $R^{n \times n}$ to $R^{m \times m}$ to make all data points live in a space of the same dimension. Then, we use the Riemannian Procrustes Analysis (RPA) [2] to match the statistical distribution of the two datasets.

We apply our method on several BCI datasets (publicly available via [3]) and demonstrate its use for Transfer Learning between different databases in addition to the classical within-databases case.

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Performance, transfer learning and underlying physiology in children playing P300 BCI games

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P300-based interfaces are widely used in BCI because they allow a selection between many choices in a relatively short time. Recently, we motivated its use for attentional training in children with ADHD (Fouillen, Maby, Le Carrer, Herbillon, & Mattout, 2017). The aim of the current study was to evaluate the performance of healthy children playing three different calibration-free P300 BCI games (Figure 1). 19 children played all three games (about 20 trials each). We counterbalanced the order of the games over children. Children were choosing freely their targets, which they were instructed to focus. A remote eye-tracker was used to record the target location. EEG-based online selection relied on template signals learned from a previously acquired database in other children playing a single and different game. All tested children here performed the task significantly well. 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. Furthermore, all children underwent an inevitable drop of performance when comparing offline (individual) with online (template based) performance. 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. We conclude that, although very different in terms of game play, all these games can be used as entertaining environments to train subjects how to control a P300 BCI. Moreover, as each of these games does involve a common process (voluntary selective attention) but also specific ones, they might prove more efficient if used in combination. Our results pertaining to the template evaluation also support the idea to use such games, without a calibration phase, in children with ADHD.

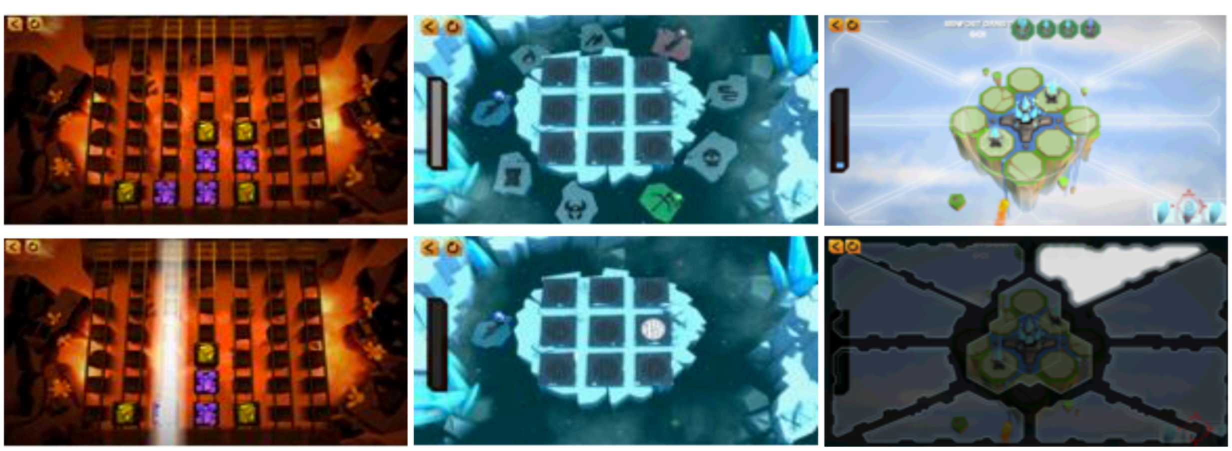

Figure 1. Screenshots of the BCI games, in the absence of flashes (top panel) and during one flash (bottom panel)

Fouillen, M., Maby, E., Le Carrer, L., Herbillon, V., & Mattout, J. (2017). ERP-based BCI training for children with ADHD: motivation and trial design. *7th Graz Brain-Computer Interface Conference 2017*. https://doi.org/10.3217/978-3-85125-533-1-26

Intracortical single unit dynamics in Broca's area during overt and covert speech

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While overt and covert speech have been shown to share overlapping neural substrates, the understanding of the detailed ensemble dynamics of either form of speech production would prove useful to the development of an intracortical speech BCI. Broca's area is a region of the inferior frontal gyrus of the dominant hemisphere known to play a major role in speech production. With the goal to study the neuronal activity of this area in relation to overt and covert speech, the intracortical activity of a neurosurgical patient was recorded using a Utah array implanted in the pars triangularis of the left hemisphere. The electrophysiological signals were recorded while the subject performed a task driven by cues on a screen. Each trial of the task consisted in reading aloud a sentence, repeating it aloud and finally repeating it covertly. Spike sorting applied to the signals of the 96 microelectrodes allowed to isolate 38 putative single units with stable activity on a portion of 33 consecutive trials. A model was trained to classify time samples between behavioral conditions (overt speech, covert speech and silence) using a relevant set of time-shifted firing rates, selected by a greedy approach. The model, evaluated by cross- validation, gave a classification accuracy above chance level, revealing that the neuronal activity was modulated according to these conditions. In particular, it was possible to classify inner speech intervals versus silence and overt intervals with more than 70% accuracy, suggesting the existence of an ensemble activity specific to inner speech. Classification using the firing rate of individual units further showed that the modulated cells had a maximum discriminative power at given time shifts around speech production onset. Interestingly, the behavioral condition at a given time was most related to the past activity of some units and to the future activity of others.

COMPUTATIONAL MODELLING TO PREDICT/EXPLAIN MI-BCI USERS' PERFORMANCES AND THEIR PROGRESSION

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Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) make use of brain signals produced during mental imagery tasks to control a computerized system. The current unreliability of MI-BCIs could be due, at least in part, to the use of inappropriate user-training procedures. In order to improve these procedures, it is necessary first to understand the mechanisms underlying MI-BCI user- training, notably through the identification of the factors influencing it. Thus, we aim at creating a statistical model that could explain/predict the mean performances of MI-BCI users using their traits (e.g., personality) but also the evolution of performances using demographic data (age, gender) and the timing of the experiment (time lapse between two sessions).

We used the data of 42 participants collected from three different studies [1–3] that were based on the same MI-BCI paradigm. They were asked to learn to control an MI-BCI by performing three MI-tasks (i.e., left-hand motor imagery, mental rotation and mental subtraction) across different training sessions (3 or 6 depending on the experiment). We used a LASSO regression (Least Ab- solute Shrinkage and Selection Operator)[4] with a leave-one-subject-out cross validation to build different models.

Our first results showed that using the users' traits may only enable the pre- diction of performances within one multiple-session experiment, but might not be sufficient to reliably predict MI-BCI performances across experiments. In a second time, we were able to find a model gathering all the subjects that could predict the mean performance of a session using the participant's gender, the timing of the experiment and the mean performance over the previous session ($p < .01$).

Further studies considering, for instance, an estimation of the users' states and new metrics to assess performances are necessary to reveal more reliable models of MI-BCI performances.

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