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Investigating the proper time to perform the motor imagery task in a multimodal BCI

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Introduction - In the paradigm of EEG motor imagery BCI, one of the challenges is to elicit brain patterns that are differentiable to ensure a good discrimination for machine learning algorithm[1]. Using a robotic arm is a way to trigger the brain into doing the motor imagery task. The degrees of freedom cannot be dealt solely by a MI BCI most of the time limited to four classes in complex and demanding for the subjects scenarios. In that context, a solution is to couple the BCI with another technology such as eyetracking [2]. This coupling allows to control the position reached by the robot's gripper via gaze and the closing of the hand via the MI task in an intuitive way closer to real directed grasping movements. In this framework; we decide to interrogate the appropriate moment to perform the MI task during a shared control between gaze and BCI.

Material, Methods and Results - We propose 3 configurations to answer the problematic: one where the task of MI/rest is performed prior to the robot's movement (Strategy 1), one after the movement (Strategy 2) and one while the robot is moving (Strategy 3). We investigate differences of performances and difference of power spectrum in the α and β bands in the sensorimotor cortex between strategies. Each strategy consists of 3 phases, one phase of calibration where subjects receive only positive feedback, the robotic arm closes its gripper at each MI task. And two phases of driving (Drive 1 & 2) where subjects receive feedback based on their neural activity (the robotic arm closes its gripper if the machine learning algorithm classifies accurately the MI task). Between phases, a LDA is trained on the feature of interest (electrodes in the sensorimotor cortex at a chosen frequency) based on the R^2 map of electrodes and frequency bands shown during the previous phase. 10 subjects(4 Males aged 25,3 $\pm$ 2,4) performed over 3 weeks the different strategies in a randomised way. Figure 1 presents the main results in terms of power spectrum contrast maps and the protocol setup. During Drive 1, we obtain in average in accuracy 63%,65% and 65% (Strat 1,2,3 respectively) and 79%,91% and 86% in sensitivity. During Drive 2, we obtain in average in accuracy 72%,75% and 75% (Strat 1,2,3 respectively) and 81%,78% and 81% in sensitivity.

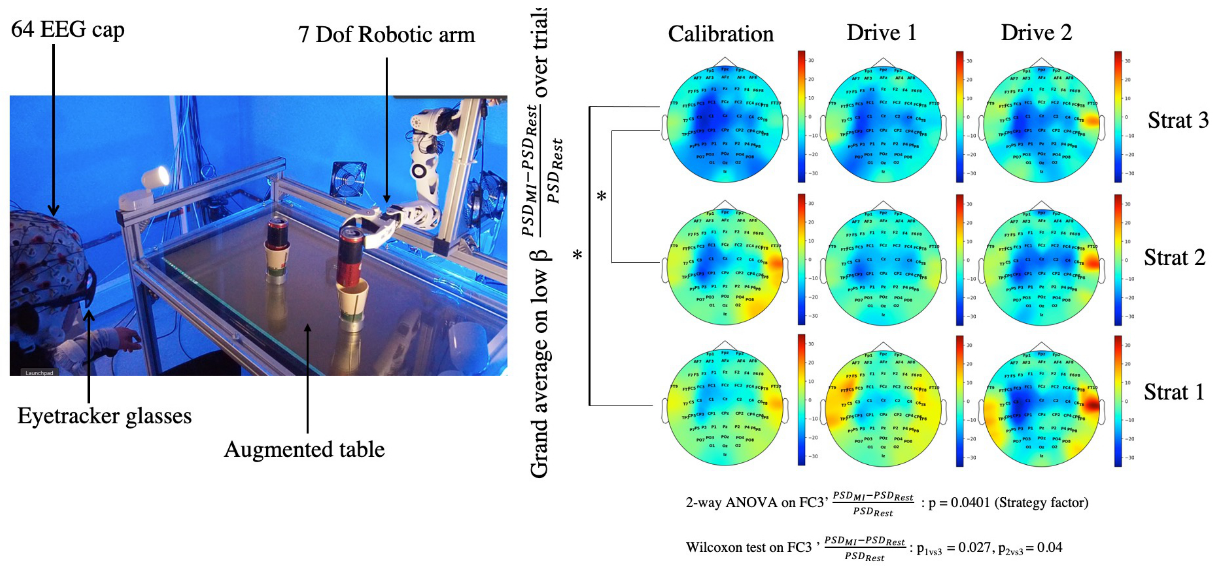

Figure 1: Left : Setup composed of the eyetracker, the robotic arm, the EEG cap and the augmented table(a red dot appears under the can for MI task and a blue dot for resting state), Right : grand average analysis of the subjects ERD on low β band (13-25 Hz)), Wilcoxon test performed on the ERD between strategies on relevant of the sensori motor cortex based on 2-way ANOVA test $p < 0.05$ between strategies.

Discussion and Significance - First, from the ERD perspective, we observe that the strategy 3 induces an activity significantly different from strategies 1 and 2. Moreover strategy three seems to activate more networked areas than the other two, meaning that having the robot moving during the MI task could induce extra cognitive process.

References

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