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Scenario screen: P300 speller variation for wheelchair control

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Introduction: The Donchin (or P300) speller is a Brain–Computer Interface developed for enabling people with severe motor disabilities to dictate words to a computer. We propose a variation on the stimulus scheme (also called *scenario screen*) which is a stimulator for controlling wheelchair navigation based on the native OpenViBE Donchin speller, but with dynamically changing image background and asymmetrically arranged stimulation markers. The image is a snapshot of the current navigation scenario and markers are located over relevant landmarks inferred from an automated scene analysis engine. In this work, we focus on the evaluation of P300 detection when the image and marker locations are different from those used for training.

Material and Methods: SCREEN IMPLEMENTATION. Our *scenario screen* is an improved version of the screen described in [1]. This version implements: single marker stimulation mode, green/blue flashes, eight landmark markers, four specific task markers placed on corners, and variable and random Inter–Stimulus Interval in six discrete steps within 125–225 ms. Three different screens (images and navigation markers) namely A, B and C implemented the aforementioned features. ACQUISITION SETUP. Eight passive Au electrodes (Fz, C3, Cz, C4, P3, Pz, P4, Oz), joint reference (A1, A2) and right mastoid reference were used. Acquisition device was a 16 channel g.USBamp with 512 Hz sample rate, passband (1.5–10.0 Hz) and notch (60.0 Hz) filters. EXPERIMENTAL PROCEDURE. Ten body–abled subjects aged 26$\pm$5.5 years participated in this protocol. Two sessions (*S0, S1*) separated between 3 and 15 days comprised the protocol. Both sessions consist on 16 copy mode repetitions of 10 trial each with homogeneous target selection. On *S0* only screen A is presented. *S1* was organized and presented to subjects in four blocks of four repetitions each. Blocks 0 and 3 showed screen A, and blocks 1 and 2 showed screen B or C. PREPROCESSING. EEG signals were filtered (41th order passband FIR, 1.5–10.0 Hz) and segmented in epochs of 307 samples. Each epoch was detrended, z–score normalized and subsampled by a factor of four. Eight channel data were concatenated. FEATURE EXTRACTION. LASSO [2] regression was used for both sparse feature selection and classification as follows. Through the LARS [3] algorithm with 15–fold cross–validation the optimal regression weights and relevant features were computed. Concatenated epochs were labeled for target and no-target respectively. CLASSIFICATION. Reduction to relevant features and projection over weights were performed on appropriately arranged data. The marker that elicits P300 on a given repetition was the minimum of the 12 accumulation of the ten trial regression results.DATA ORGANIZATION. Train data were the first eight repetitions of *S0*. Already calculated weights were directly utilized for classifying the unseen data from three groups: G0 last eight repetitions of *S0*, G1 blocks 0 and 1, and G2 blocks 1 and 2 of *S1*. On each group, sensitivity and specificity were computed as performance metrics. EVALUATION. Kruskal–Wallis H test was computed for sensitivities among the three groups in order to test whether changes on the image background and marker positions impact on the performance detection of P300. A similar test was made for specificities.

Results: There was no evidence to reject that sensitivity is statistically equal for all groups with $p > 0.15$ and medians 1.00, 0.75, 0.88 (IQR = 0.78–1.00, 0.47–0.88, 0.50–0.97). Similar results were obtained for specificity with medians 1.00, 0.98, 0.99 (IQR = 0.98–1.00, 0.95–0.99, 0.95–1.00).

Discussion: As the results suggest, the image and marker location do not impact on the classification performance, even for unseen screens. In other words, LASSO feature extraction and cumulative classification demonstrated to be robust given their tolerance to inter–session time, and image and marker location changes. Additional analysis has to be made on the temporal behavior of the detections since some subjects reach lower performances on the very last repetitions. However, there were subjects whose performance increased on the unseen screens.

Significance: The robustness of the P300 detection gives evidence to the potential application of the *scenario screen* on a real wheelchair navigation task. On the other hand, the results are consistent with the fact that P300 are potentials related to the stimulus perception and not to the screen appearance, however, more research should be made in this sense.

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