Preliminary results on P300 detection using machine learning when modulating task reaction time

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Introduction:

In recent years, machine learning (ML) method has been applied to detect cognitive states [1], e.g. the event-related potential (ERP) P300 has been often used for BCI applications [2]. The P300 correlates to cognitive processing elicited by successful recognition of important messages [3, 4]. Unlike most BCIs (e.g. P300 speller), the application in the robotic field requires to detect more naturally evoked ERP activity during multiple tasking. We developed a scenario requiring a main task (e.g. manipulating) and a secondary task (recognition of important warnings). Previous results proved a successful P300 detection in such complex scenarios [5]. However, in a real scenario, it is not always possible to react to important information immediately. The goal of the study was to investigate the performance of P300 detection during delayed reaction to warnings.

Methods:

6 data sets (120 targets and 720 standard stimuli for each set) were acquired from two subjects during multiple tasking in a virtual environment (see Fig. 1). EEG was recorded with a 64 electrode actiCap system and BrainAmp DC amplifiers (Brain Products GmbH) with reference at FCz. Two electrodes (TP7/TP8) were used to measure muscle activity and excluded for data analysis. For ML and ERP analysis, the data was divided into 5 groups based on reaction time (ms): 1400, 1600, 1800, 2000, and 5000.
For ML analysis, the recorded 6 EEG data sets from two subjects were merged into one data set for each subject (details for preprocessing, see Fig. 2). The data was resampled 10 times using bootstrapping by random selection of 60 training examples for target class. We used xDAWN [6] as a spatial filter to enhance signal-to-noise ratio. Amplitude values were transferred to normalized features to train the classifier. For classification of standards and targets, we used a linear support vector machine (SVM) [7]. Balanced accuracy (i.e. mean of true positive rate and true negative rate) was used as performance metric.
To find how the reaction time affects the classification performance, the data was analyzed by repeated measures ANOVA with reaction time (RT) as a within-subjects factor. For pairwise comparisons, Bonferroni correction was applied. The observed amplitude difference (ERP analysis see Fig. 3) between targets and standards was not statistically analyzed due to small sample sizes.

Results:

Figure 2 shows the effect of reaction time on the classification performance (main effect of reaction time: $F(4, 76) = 21.585$, $p < 0.001$). Best classification performance was obtained from the shortest RT, which significantly differed from the classification performance of middle and long RT but not from the second shortest [RT 1400 vs. RT 1800: $p < 0.037$, RT 1400 vs. RT 2000: $p < 0.006$, RT 1400 vs. RT 7000: $p < 0.001$, RT 1400 vs. RT 1600: p = n.s.]. The longest RT led to worst classification performance which differed significantly from all RT conditions [$p < 0.001$].

Conclusions:

Our results suggest that the delay of reaction time to perform the task has an influence on the classification performance of P300 detection. That means, there could be a difference between the normally quick response to targets and the delayed response to targets during multiple tasking. These results are preliminary. We need more data from more subjects to ensure that the delayed task time generally affects the classification performance of P300 detection. The possible reason for the decrease of classification performance could be related to the preparation of movement (pressing the buzzer). After recognizing the targets, we assume the motor preparation begins. In our previous results, we could predict movements (e.g. detection of lateralized readiness potentials (LRP)) [8]. It is interesting to investigate how the delay of task reaction time can be related to the classification performance of movement prediction. Further, the possible influence of movement prediction can be investigated in relation to performance of P300 detection.

Motor Behavior:

Brain Machine Interface

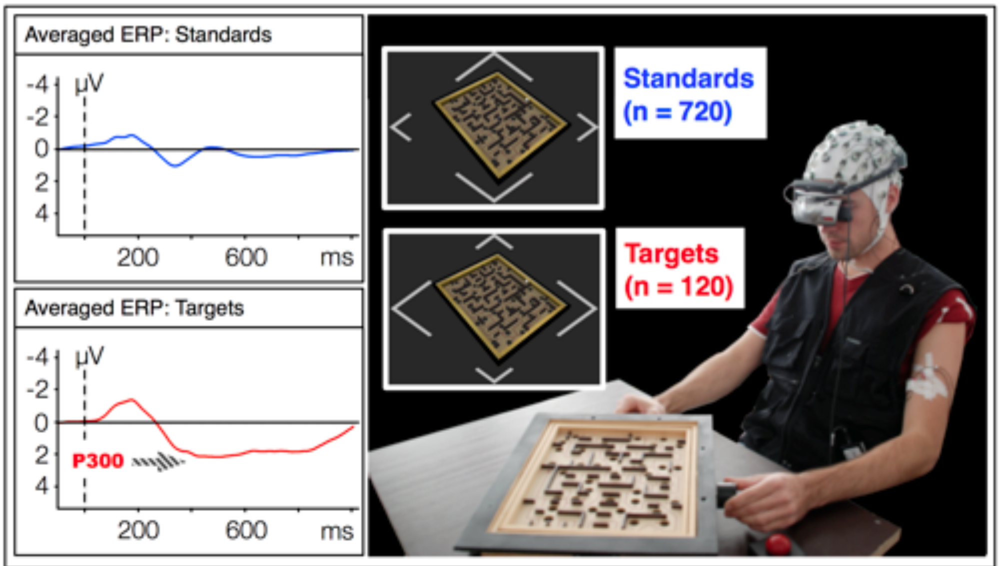

Fig. 1 Experimental Setup: *Right:* Subjects plays a physical simulation of the Labyrinth game and responds to target stimuli, which are mixed among frequent "standard" stimuli with a ratio of 1:6 and an inter-stimulus-interval of 1000 +/-100 ms, by pressing a buzzer. Subjects were instructed to wait to respond to target stimuli. *Left:* event-related potentials (ERP) elicited by "targets" and "standards". Each data set contains 120 target stimuli and 720 standard stimuli. Only artifact-free trials were averaged based on stimulus type (standards and targets).

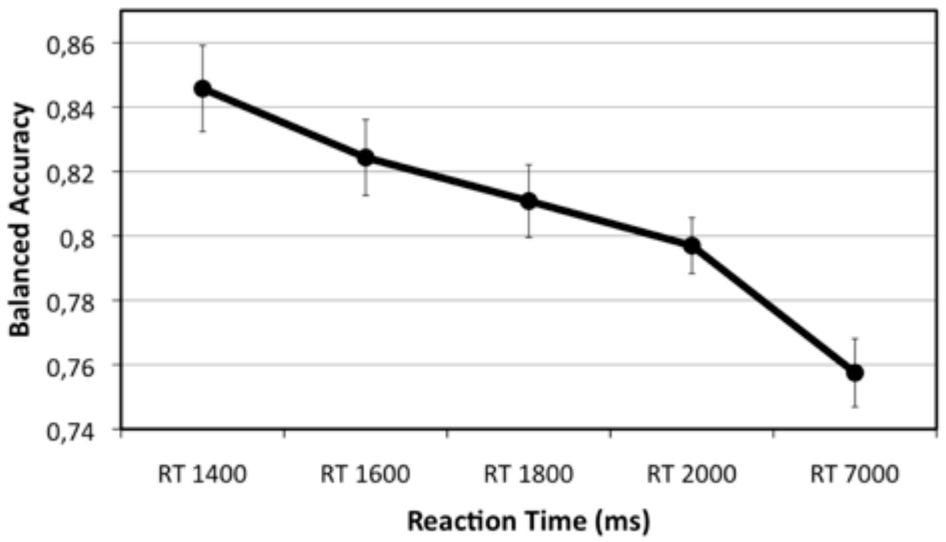

Fig. 2 ML results: Classification performance of P300 detection using ML methods. The more the task reaction time (RT) is delayed, the less the classification performance.

Preprocessing: the data was windowed (epochs from 0 to 1000 after stimulus onset), standardized (mean=0, SD=1), decimated to 25 Hz and filtered with a low pass of 4 Hz.

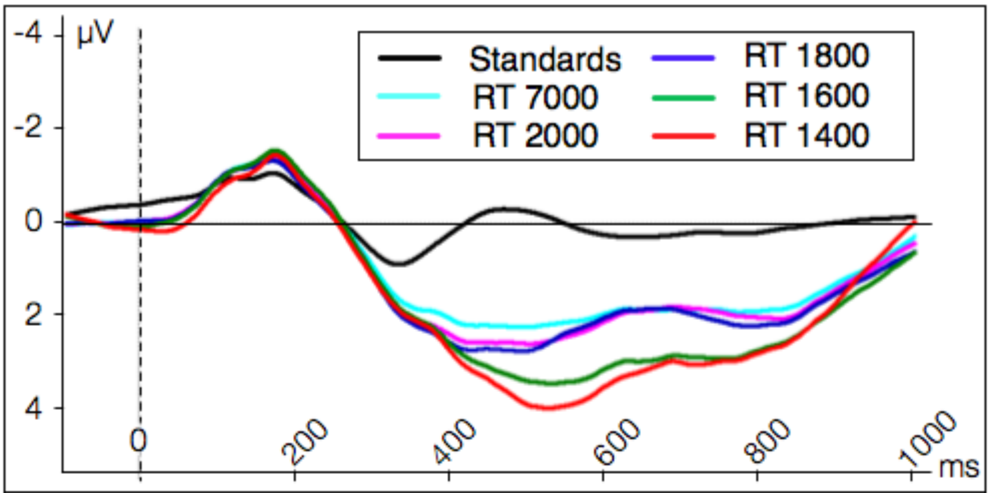

Fig. 3 ERP results: Grand Average ERPs elicited by targets and standards. Only artifact-free trials were averaged based on stimulus type (standards and targets). The colored ERPs were 5 different groups of targets which were generated based on the reaction time from target recognition to pressing the buzzer as a response to targets. The intensity of P300 was reduced by the delay of the response.

Preprocessing: EEG was re-referenced to an average reference and filtered with a bandpass (0.1-4Hz). After artifacts rejection, the data was segmented into epochs from 100 ms before stimulus onset to 1000 ms after stimulus onset. Epochs were averaged based on stimulus type (standards and targets). Like ML analysis, the target trials were divided by 5 groups based on the reaction time.

Abstract Information

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