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Effects of performing two visual tasks on single-trial detection of event-related potentials

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Abstract— **The detection of event-related potentials (ERPs) in brain-computer interface (BCI) depends on the ability of the subject to pay attention to specific stimuli presented during the BCI task. For healthy users, a BCI shall be used as a complement to other existing devices, which involve the response to other tasks. Those tasks may impair selective attention, particularly if the stimuli have the same modality *e.g.* visual. It is therefore critical to analyze how single-trial detection of brain evoked response is impaired by the addition of tasks concerning the same modality. We tested 10 healthy participants using an application that has two visual target detection tasks. The first one corresponds to a rapid serial visual presentation paradigm where target detection is achieved by brain-evoked single-trial detection in the recorded electroencephalogram (EEG) signal. The second task is the detection of a visual event on a tactical map by a behavioral response. These tasks were tested individually (single task) and in parallel (dual-task). Whereas the performance of single-trial detection was not impaired between single and dual-task conditions, the behavioral performance decreased during the dual-task condition. These results quantify the performance drop that can occur in a dual-task system using both brain-evoked responses and behavioral responses.**

I. Introduction

Non-invasive Brain-computer interfaces (BCIs) based on the detection of event-related potentials (ERP) typically require subjects to perform a specific task in order to produce a robust and detectable neural response in the electroencephalogram (EEG) signal (*e.g.* ERP based spellers [1], [2]). Contrary to severely disabled persons where a BCI can represent the only mean of communication [3], BCIs are often used as a complement to other interfaces, *e.g.* joystick, keyboard,... [4]. Therefore, subjects have to divide their attention across several types of stimuli and tasks: the stimuli for evoking ERP, the stimuli related to the feedback of the BCI task, and the stimuli from additional tasks. A long line of studies in cognitive psychology has demonstrated that performing multiple tasks at, or near, the same time results in behavioral performance decrements and modulations in neural activity compared to when one task is done in isolation [5], [6]. In the present work, we focus on the effects of performing multiple tasks on single-trial detection of event-related potentials.

Several recent studies have investigated the effects of dual-task performance on single-trial detection when the two tasks are presented in different sensory modalities (auditory and visual) [7], [8]. In contrast, here we focus on the effects of dual-task performance when both tasks being performed are presented in the visual modality. In the present study, two visual tasks were presented on a computer screen. In one task observers monitored realistic scenes displayed in rapid serial visual presentation (RSVP) for images containing a target (person). In the other task, observers monitored a map for the presentation of a green dot and were to press a button when the dot was presented. Observers either performed these tasks alone (single task) or at the same time (dual task) and the goal was to investigate the impact of increasing the visual workload on single trial detection of the target stimulus in the RSVP task. Based on the previous literature showing that the latency, amplitude, and spatial distribution of ERP components, like the P300, are modulated by the attentional demands of dual-task performance [9], [10], it is reasonable to hypothesize that single-trial detection should be impaired under dual task conditions.

The rest of the paper is organized as follows. The experimental protocol and the different conditions are presented in the second section. The signal processing methods for single-trial detection is detailed in the third section. The behavioral and single-trial detection performance are presented in the fourth section. Finally, the relevance of this study for ERP based applications in multi-task conditions is discussed in the last section.

II. Experimental protocol

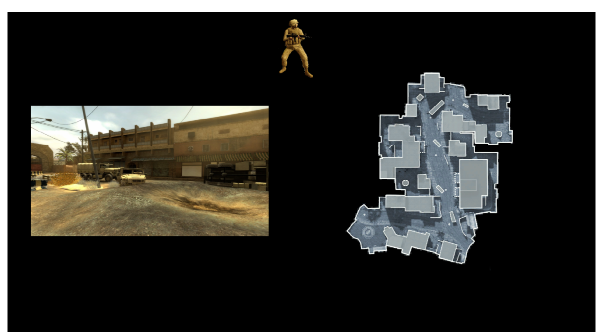

Fig. 1. RSVP task (left) and Map task (right).

The experiment represents a simulation of potential tasks that could be performed in manned ground vehicles. Indeed, the impact of the increasing visual workload on small crew should be investigated to better understand the performance drop that can be observed by performing two visual tasks. The paradigm was composed of two tasks: an RSVP task and an event detection task on a map (Map task):

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1) RSVP task. The stimuli consisted of 300 color images (683×384 pixel). These images were taken from "Insurgency: Modern Infantry Combat" (Insurgency Team), a total conversion modification of the video game "Half-Life 2" (Valve corporation). The realistic images were separated into two groups: target images (100 images), which contains a person, and non-target images (200 images), which does not contain anyone. The images were presented on the left side of the screen centered $\approx 13^o$ to the left of fixation, as depicted in Figure 1, and at a frequency of 5Hz. The task was to detect the presence of a person, but not to give a motor response. Target probability was 10%, with an average inter target interval of 2s.
2) Map task. The visual stimuli consisted of the image of a tactical map that may contain a green dot. The images were presented on the right side of the screen centered $\approx 13^o$ to the right of fixation, as depicted in Figure 1. The task was to press a button when a green point was presented somewhere on the map. The green point can be presented at different positions on the map. The average inter stimulus interval was set to 8s.

Ten healthy subjects, recruited through the University of California, Santa Barbara (UCSB) online subject recruitment system, completed the experiment (mean=20.0 years, sd=1 - 6 females). Participants gave informed consent and received course credit for their participation (credit was not contingent on any element of task performance). All procedures were approved by the UCSB Human Subjects Committee. Each participant seated 60cm from the computer screen (visual angle $\approx 27^o$), and performed the tasks under three attention conditions, two single-task conditions (STC), and a dual-task condition (DTC):

1) In the RSVP-only task, participants were instructed to only perform the target detection task, *i.e.* to pay attention to the RSVP task.
2) In the Map-only task, participants were instructed to only respond to the events appearing on the map.
3) In the dual-task condition, participants were instructed to simultaneously perform the RSVP task and the Map task. Subject were instructed to give the tasks equal priority.

Each subject performed two sessions for each condition. The order of the conditions was counterbalanced across participants. For each session, the number of trials for targets and non-targets was 192 and 1728 in the RSVP task, respectively. For the Map task, there were 48 events per session.

III. Methods

A. Signal acquisition

The EEG signal was measured for each subject from 32 Ag/AgCl sintered electrodes mounted in an elastic Biosemi headcap with active electrodes. The 32 electrodes were sub-sampled from the 10-10 system [11]. Additional electrodes were placed at the right and left mastoids, as well as 1 cm lateral to the left and right external canthi (horizontal), and above and below each eye (vertical) for the electro-ocologram (EOG). A Biosemi ActiveTwo EEG amplifier was used for recording the signal. The EEG signal was sampled at 256Hz and referenced offline to the average mastoid signal.

B. Signal processing

First, the EEG signal was bandpassed filtered (Butterworth filter of order 4) with cutoff frequencies at 1 and 10.66Hz. Then, the signal was downsampled to obtain a signal at a sampling rate equivalent to 32Hz. For the next processing steps, we considered the observed signal over 612ms after the start of a visual stimulus (20 sampling points). The following step consisted of enhancing the relevant signal with spatial filters. Let us denote by $U \in \mathbb{R}^{N_s \times N_f}$, the spatial filters, where N_s is the total number of electrodes and N_f is the number of spatial filters. The signal after spatial filtering is defined by $X_{filt} = XU$ where $X \in \mathbb{R}^{N_t \times N_s}$ is the recorded signal, N_t is the number of sampling points. We consider here the xDAWN algorithm [12]. This method has been applied in P300 based BCI and in RSVP tasks with good performance [13], [8], [14]. An algebraic model of the enhanced signals XU is composed of three terms: the ERP responses on a target class (D_1A_1), a response common to all stimuli, *i.e.* all targets (images with a person) and non-targets (images without a person) confound (D_2A_2), and the residual noise (H), that are all filtered spatially with U.

$$XU = (D_1A_1 + D_2A_2 + H)U. \tag{1}$$

where D_1 and D_2 are two real Toeplitz matrices of size $N_t \times N_1$ and $N_t \times N_2$, respectively. D_1 has its first column elements set to zero except for those that correspond to a target onset, which are represented with a value equal to one. For D_2, its first column elements are set to zero except for those that correspond to stimuli onset. N_1 and N_2 are the number of sampling points representing the target and superimposed evoked potentials, respectively. H is a real matrix of size $N_t \times N_s$. We define spatial filters U that maximize the signal to signal plus noise ratio (SSNR):

$$\text{SSNR}(U) = \text{argmax}_{\,U} \frac{Tr(U^T \hat{A}_1^T D_1^T D_1 \hat{A}_1 U)}{Tr(U^T X^T X U)} \tag{2}$$

where $\hat{A}_1$ represents the least mean square estimation of A_1 :

$$\hat{A} = \begin{bmatrix} \hat{A}_1 \\ \hat{A}_2 \end{bmatrix} = ([D_1;D_2]^T[D_1;D_2])^{-1}[D_1;D_2]^T X \tag{3}$$

where $[D_1;D_2]$ is a matrix of size $N_t \times (N_1+N_2)$ obtained by concatenation of D_1 and D_2. Spatial filters are obtained through the Rayleigh quotient by maximizing the SSNR [12]. For the classifier input, we used four spatial filters ($N_f = 4$). The input vector was obtained by the concatenation of the N_f time-course signals across spatial filters. The Bayesian linear discriminant analysis (BLDA) classifier was used for the detection of the ERPs [15], [16].

C. Performance evaluation

The hit-rate, or true positive rate and the precision are considered as a measure for the behavioral performance. They are defined as follows:

$$\text{True positive rate (TPR)} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{Precision (PPV)} = \frac{TP}{TP + FP} \quad (5)$$

where TP, FP, and FN are the number of true positive, false positive, and false negative, respectively. Furthermore, a behavioral response was considered as correct if the target was presented to the user less than 1s before the user pressed a button. For the performance evaluation of single-trial detection, we consider the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) [17].

IV. Results

A. Map task

The mean and the standard error of the behavioral performance, for each subject, and for both STC and DTC, are presented in Figures 2 and 3. The mean hit-rate was 91.30% and 86.60% for STC and DTC, respectively. A pairwise t-test revealed that the hit-rate in STC was superior than during DTC ($t_{(9)} = 2.391$, $p < 0.05$). The mean precision was 97.23% and 92.36% for the STC and DTC, respectively. Paralleling the pattern of performance measured by the hit rate, a pairwise t-test indicated that the precision in STC was also superior than in DTC ($t_{(9)} = 2.868$, $p < 0.05$).

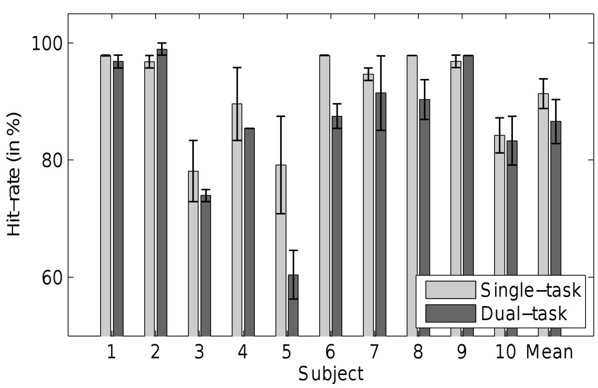


Fig. 2. Behavioral performance: hit-rate (Map task).

B. RSVP task

The mean and the standard error of the single-trial detection performance, for each subject and each condition, is presented in Figure 4. The mean AUC across subjects was 0.837 and 0.838 for STC and DTC, respectively. A pairwise t-test showed that there is no difference between the two conditions ($t_{(9)} = 0.040$, $p = 0.968$). This indicated that the addition of the secondary task (the Map task) had no influence on the performance of single-trial detection. The ROC curves for both STC and DTC are depicted in Figure 5.

The spatial distribution for STC and DTC are presented in Figure 6. The spatial distribution is based on the first spatial

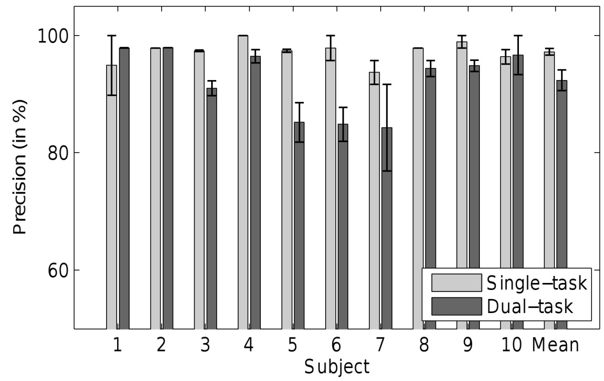


Fig. 3. Behavioral performance: precision (Map task).

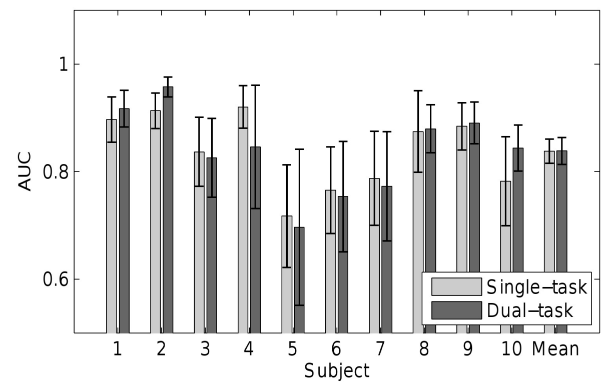


Fig. 4. AUC (RSVP task).

filter of the xDAWN method [12]. These results show the large variability both across subjects and conditions.

V. Discussion and conclusion

The results allowed us to determine several key points: first, it is possible to efficiently use single-trial detection for visual target detection in both STC and DTC, and second DTC do involve a drop of performance for one of the task. The first point is encouraging for integrating an RSVP system in multitask settings. The second point confirms the hypotheses mentioned in the introduction that the overall performance in DTC can be degraded. Although a drop of performance was observed, this decrease of performance was only observed in one task where the performance was already high. These results confirm the outcome of a previous study combining visual and auditory stimuli where the drop of performance was observed on the easiest task, *i.e.* the task requiring the lesser attention [8]. Given the highest difficulty of the RSVP task compared to the Map task, we hypothesize that the drop of performance for the Map task during DTC was due to a shift of attention from the easy task to the most difficult task.

Transferring the BCI technology from a demonstrator to a commercial application remains a challenge for several reasons. To leverage the use of ERP based applications, investigations should be carried out in several directions. It does not only concern hardware (amplifiers, electrodes)

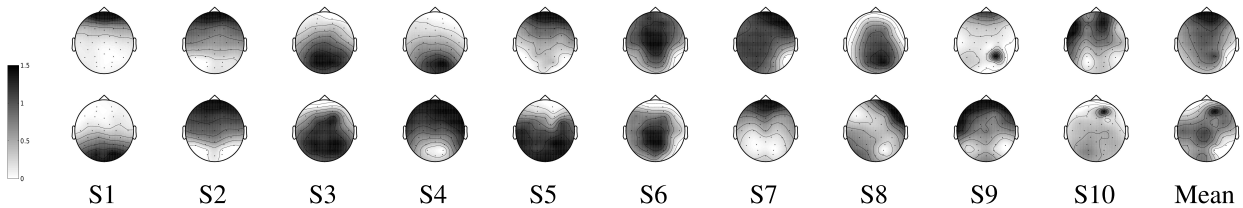
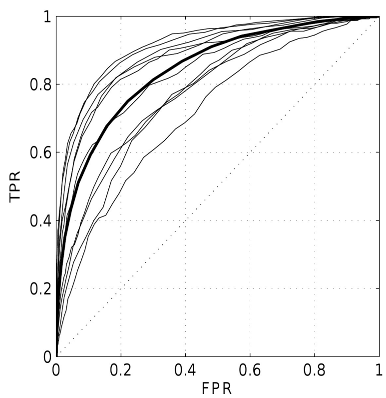
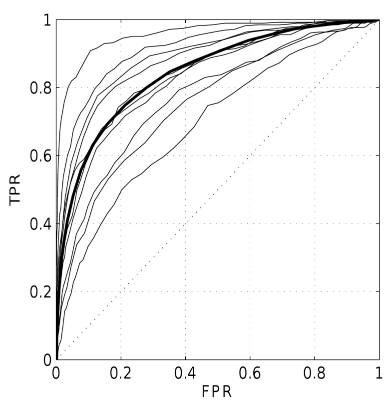


Fig. 6. Spatial distribution based on the spatial filters [12] (top: STC, bottom: DTC).



(a) STC - mean AUC=0.837



(b) DTC - mean AUC=0.838

Fig. 5. ROC curves of each subject. The bold line represents the mean ROC curve.

and software (machine learning methods) but also how ERP based applications can be successfully transposed to a clinical and/or commercial product. Indeed, an ideal system should be asynchronous [18] and reliable in difficult conditions *e.g.* dual-task condition. In this study, we have shown that a target detection system based on the ERP detection could be successfully incorporated in a system with other tasks being performed in parallel. Further works will investigate the impact of task difficulty for estimating how different tasks with various difficulties may interact while being performed simultaneously.

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