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Enhancing Single-Trial Mental Workload Estimation through xDAWN Spatial Filtering

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***Abstract*— Mental state monitoring is a topical issue in neuroengineering, more particularly for passive brain-computer interface (pBCI) applications. One of the mental states that are currently under focus is mental workload. The level of workload can be estimated from electroencephalographic activity (EEG) and markers derived from this signal. In active BCI applications, a well-known neurophysiological marker, the event-related potential (ERP), is commonly enhanced using a spatial filtering step. In this study, we evaluated how a spatial filtering method such as the xDAWN algorithm could improve mental workload classification performance. Twenty participants performed a Sternberg memory task for 18 minutes with pseudo-randomized trials of low vs. high workload (2/6 digits to memorize). Three signal processing chains were compared on their performance to estimate mental workload from the single-trial ERPs of the test item (i.e. present/absent in the memorized list). All 3 included an FLDA classifier with a shrinkage covariance estimation and a 10-fold cross-validation. One chain used the ERPs of a relevant electrode for workload estimation (Cz) and the 2 others used the ERPs of the 32 electrodes and an xDAWN spatial filtering step with either 1 or 2 virtual electrodes kept for classification. Statistical analyses revealed that spatial filtering significantly improved mental workload estimation, with up to 98% of correct classification using the xDAWN algorithm and 2 virtual electrodes.**

I. Introduction

Neuroengineering is a growing research field which encompasses mental state monitoring (MSM). Such monitoring is performed by what has recently been named passive Brain-Computer Interfaces (pBCI), systems that perform mental state estimation thanks to neurophysiological markers and feature translation algorithms [1]. Those pBCIs provide new means to enhance and supplement the human computer interaction, with a major interest for safety applications. Mental workload, which can be defined as the amount of mental resources engaged in a task, and more generally as task's difficulty [2], is currently under focus for e-learning and driving applications [3].

For active BCI systems it is common to use spatial filtering methods such as Common Spatial Pattern (CSP) filters to improve classification performances of electro-encephalography (EEG) data [4]. This is done using epochs of band pass filtered signal, and then classification is carried out using features such as the log variance of this signal. Furthermore, several active BCI systems use event-related potentials (ERPs) as features. To increase classification performance using these markers, they often encompass spatial filtering steps, e.g. using the xDAWN algorithm which has originally been developed for the P300 speller application [6].

Usually, pBCIs make use of tools developed for active BCIs. As regards CSP filtering, it has been applied to estimate mental workload from several power bands by Roy and collaborators, but with only 65.51% of correct classification [5]. Moreover, to our knowledge, when pBCI systems use markers such as ERPs, they seldom perform spatial filtering. Yet, it has recently been done in affective computing with promising results. Indeed, Mathieu and collaborators demonstrated that a spatial filtering method such as the xDAWN algorithm could be used to enhance arousal estimation for negative emotions with up to 87% of correct classification [7]. But then they used peak values as features, therefore adding a computational step which can be costly in terms of real-life applications. It seems important to try and perform such a classification directly on the whole single-trial ERP and compare the classification performances between a chain that does not include the spatial filtering step and a chain that does. Also, it should be interesting to evaluate the use of such a spatial filtering method for other states than affective states, such as mental workload.

This study was designed to assess whether a spatial filtering method such as the xDAWN algorithm could enhance mental workload classification at the single-trial level. Mental workload was manipulated by varying the number of digits in memory in a classical Sternberg memory task. Three classification processing chains were compared, one that performed classification directly on the ERP signal of one electrode, and two that included a spatial filtering step and performed classification either on one or two virtual electrodes.

II. Methods

This research was promoted by Grenoble's clinical research direction (France) and was approved by the French ethics committee (ID number: 2012-A00826-37).

A. Experimental design

Mental workload was manipulated using a Sternberg memory task [8]. At each trial, the 20 healthy participants (9 females; M = 25, S.D. = 3.5 years) had to memorize a list of sequential digits visually presented on a computer screen. Then, a test item flanked with question marks was presented

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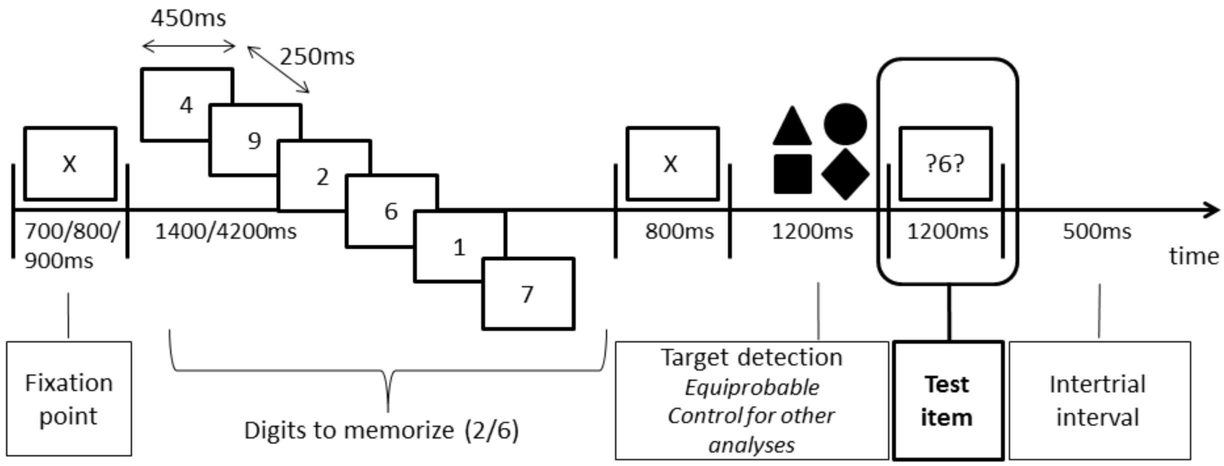

Figure 1. Trial structure. Participants have to memorize 2 or 6 digits and then answer whether the test item was present in the memorized list. The circled segment indicates the item on which the analyses were focused.

(Fig. 1). The participants had to answer as quickly as possible whether this test item was present or not in the memorized list using a response box. Two levels of workload were considered, i.e. 2 and 6 digits to memorize (low and high workload respectively). This paradigm was performed during 18 minutes, and included 72 trials of each workload level which were pseudo-randomly presented.

B. *Data acquisition & pre-processing*

Participants' performance to the test item, i.e. reaction times and accuracy were recorded, along with their EEG activity using a BrainAmp™ system (Brain Products, Inc.) and an Acticap® equipped with 32 Ag-AgCl active electrodes positioned according to the extended 10-20 system. The reference and ground electrodes used for acquisition were those of Acticap, i.e. FCz for the reference electrode and AFz for the ground electrode. The data were sampled at 500 Hz. The electro-oculographic (EOG) activity was also recorded using 2 electrodes positioned at the eyes outer canthi, and 2 respectively above and below the left eye.

The EEG signal was band-pass filtered between 1 and 40 Hz, re-referenced to a common average reference and corrected for ocular artifacts using the signal recorded from the EOG electrodes and the SOBI algorithm [9]. It was also down-sampled to 100Hz. The ERPs were extracted by epoching the EEG signal from 200ms before stimulus onset to 600ms after stimulus onset (test item). Three processing chains were considered and the features used for classification were the ERPs from:

1) One channel (Cz), no spatial filter;
2) One virtual electrode computed from the 32 electrodes;
3) Two virtual electrodes computed from the 32 electrodes.

Hence, one processing chain was based solely on the ERPs from the Cz electrode which is a relevant electrode for workload estimation [10]. In order to be fed to the spatial filtering algorithm, the data were concatenated to form an s-by-e matrix (s: number of samples, e: number of electrodes) by placing all the trials end to end.

C. *Spatial filtering*

We used the xDAWN algorithm to enhance the discrimination between the ERPs of the test item in a low and in a high workload condition. The xDAWN algorithm works as follow. The generative EEG signal model is given by:

$$\mathbf{X} = \mathbf{D}_1\mathbf{P}_1 + \mathbf{D}_2\mathbf{P}_2 + \mathbf{N} \tag{1}$$

where $\mathbf{X}$ is the s-by-e EEG matrix with s the total number of samples, and e the number of EEG channels. $\mathbf{D}_1$ and $\mathbf{D}_2$ are Toeplitz binary sparse matrices with the following dimension: s-by-s_trial (s_trial: number of samples for one trial). $\mathbf{P}_1$ and $\mathbf{P}_2$ correspond to the stereotypical evoked response matrices of dimension s_trial-by-e and $\mathbf{N}$ is the additional noise term. Therefore, $\mathbf{D}_1\mathbf{P}_1$ corresponds to the specific ERP responses for the high workload condition, whereas $\mathbf{D}_2\mathbf{P}_2$ corresponds to the common response for all conditions (low and high workload). The equation (1) can also be written as follow:

$$\mathbf{X} = (\mathbf{D}_1 \quad \mathbf{D}_2)\begin{pmatrix}\mathbf{P}_1\\ \mathbf{P}_2\end{pmatrix} + \mathbf{N} = \mathbf{DP} + \mathbf{N} \tag{2}$$

The stereotypical responses contained within $\mathbf{P}$ are estimated by solving the following problem in the least squares sense:

$$\widehat{\mathbf{P}} = \min_{\mathbf{P}}\|\mathbf{X} - \mathbf{DP}\|_F^2 \tag{3}$$

Next, the spatial filters are computed by maximizing the Rayleigh quotient:

$$\rho(\mathbf{w},\mathbf{X}) = \frac{\mathbf{w}^T\left(\mathbf{D}_1\widehat{\mathbf{P}}_1\right)^T\mathbf{D}_1\widehat{\mathbf{P}}_1\mathbf{w}}{\mathbf{w}^T\mathbf{X}^T\mathbf{X}\mathbf{w}} \tag{4}$$

This quotient is maximized by solving a generalized eigenvalue problem. The xDAWN filters are designed to enhance the ratio between the signal and the signal plus noise ratio (SSNR);$\rho(\mathbf{w},\mathbf{X})$. The spatially filtered signal z, made of what we call 'virtual sensors', can then be obtained by applying the weights, or spatial filters $\mathbf{w}$ onto the data $\mathbf{X}$:

$$\mathbf{z}_k = \mathbf{X}\mathbf{w}_k \tag{5}$$

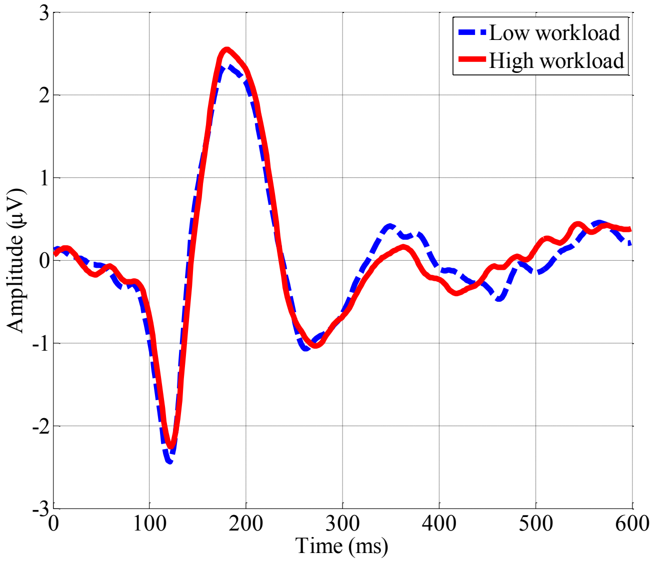

Figure 2. Grand average event-related potentials of the test item at electrode Cz depending on workload condition.

D. Classification & Analyses

Our whole processing chain consisted of a pre-processing step, the spatial filtering step if required, and then a subject-specific classification step. The classification step was similar for the 3 chains and was performed using a Fisher Linear Discriminant Analysis (FLDA), with a shrinkage covariance estimation [11] and a 10-fold cross-validation. At 100 Hz we had 60 samples per trial. As mentioned earlier we had 72 trials per workload level. Therefore, for the 10-fold cross-validation process we had 65 trials per workload level to train the classifier, and 7 to test it. We compared the performances obtained using the 3 processing chains mentioned earlier (B.).

For both the first 2 chains, 60 features were used for classification. For the 3rd chain, given that 2 virtual electrodes were considered, 120 features were used for classification. Both behavioral performances and classification results were compared using repeated measures ANOVAs and Tukey post-hoc tests. Classification performances were also compared against chance level using single means t-tests. The significance level was set at 0.05.

III. Results

A. Behavior & ERPs

Participants were slower to respond (m_{1_RT} = 490.29ms; sd_{1_RT} = 53.61ms; m_{2_RT} = 583.78ms; sd_{2_RT} = 57.74ms) and had a lower accuracy (m_{1_ACC} = 0.98; sd_{1_ACC} = 0.05; m_{2_ACC} = 0.89; sd_{2_ACC} = 0.09) in the high workload condition than in the low one ($p<0.001$). Moreover, the grand average ERPs of the test item on the Cz electrode revealed several components in accordance with the literature, i.e. the N1, P2, N2 and P3 components (Fig. 2).

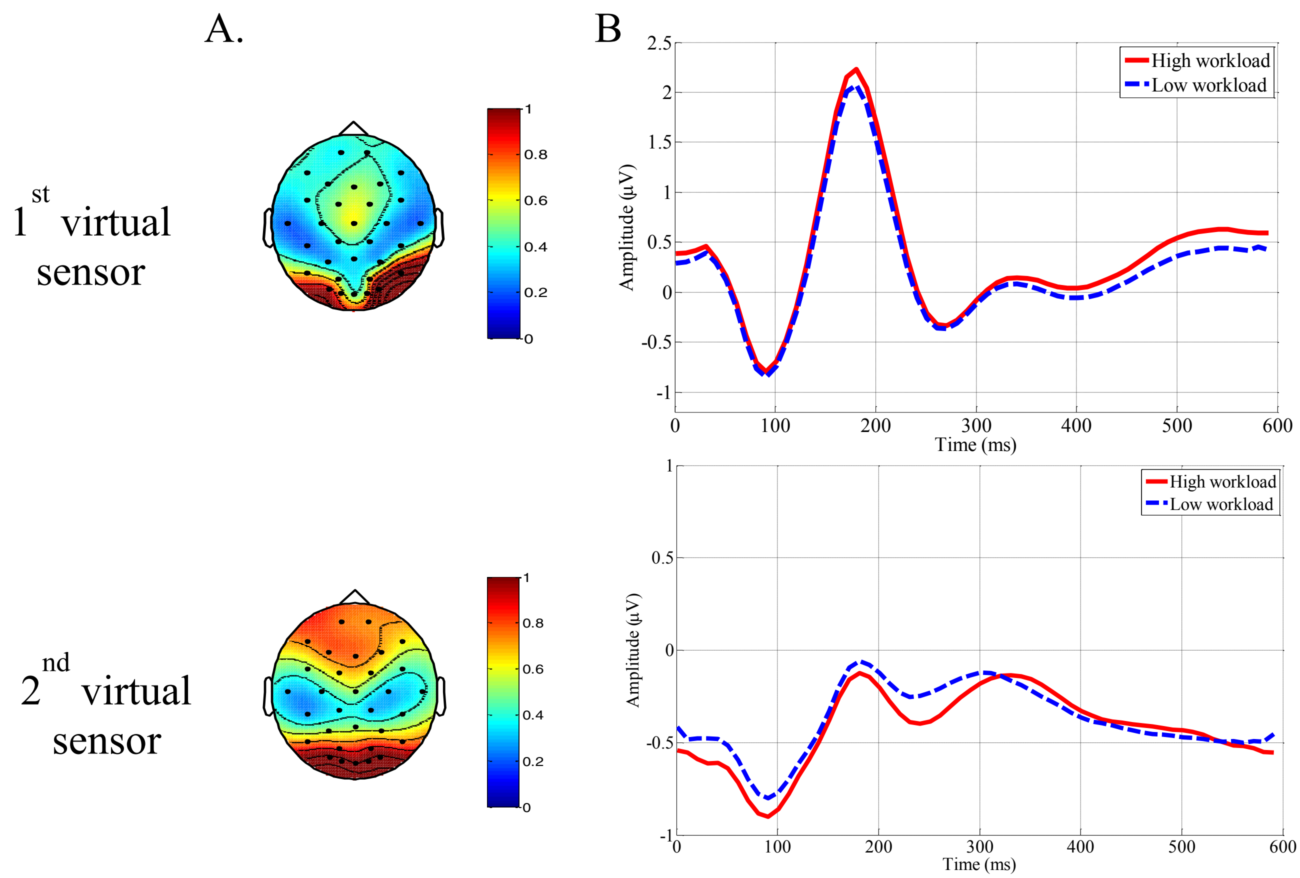

Figure 3. First two spatial filters computed using the xDAWN algorithm: A. Spatial patterns (absolute value); B. Grand average event-related potentials.

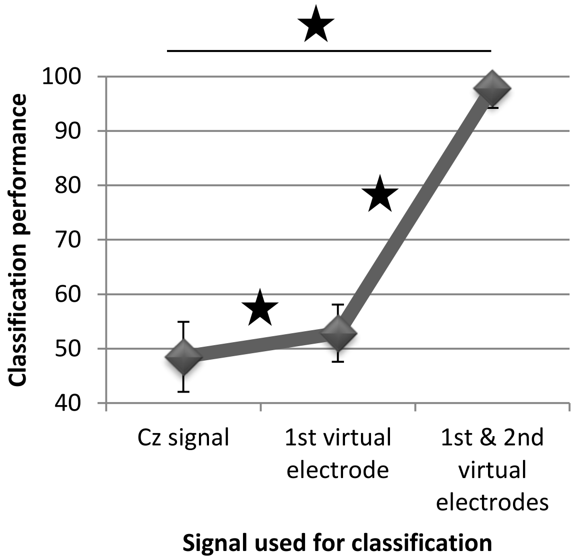

Figure 4. Mental workload estimation performance depending on the signal used for classification. *Average across participants; a star indicates a significant difference (p<0.001).*

B. Spatial filters

For the two processing chains that included a spatial filtering step, the xDAWN spatial filters considered for classification were the 1st and 1st and 2nd filters that had the highest associated eigenvalue. The grand average ERPs and spatial patterns of those filters are given in Fig. 3. Both ERPs of the filters clearly display components that are temporally related to the N1, P2, N2 and P3 components. Their spatial patterns also reveal an important implication of the electrodes placed on the parieto-occipital region, which is consistent with the processing of visual stimuli. Furthermore, they reveal that the fronto-central region is also implicated for mental workload classification, which is consistent with working memory processing.

C. Classification

Fig. 4 illustrates the mental workload estimation performances depending on the signal used for classification (m_1 = 48.48%; sd_1 = 6.43%; m_2 = 52.85%; sd_2 = 5.25%; m_3 = 97.89%; sd_3 = 3.66%). There was a significant enhancement of classification performance thanks to the spatial filtering step. Indeed, classification performance significantly increased from chain #1 to chain #2, and from chain #2 to chain #3 ($p<0.001$).

Moreover, the performance of the chain that used the Cz signal was not significantly different from the chance level ($p=0.30$), whereas both chains that included a spatial filtering step were ($p<0.05$ and $p<0.001$ respectively).

IV. DISCUSSION

Mental workload estimation can be achieved using event-related potentials as neurophysiological markers. To enhance single-trial classification performance, spatial filtering is commonly done in active BCIs and has proven to be particularly efficient. However, it is seldom performed for passive BCI applications. In this study, we assessed the importance of enhancing the contrast between workload conditions using a spatial filtering step. The algorithm we used, xDAWN, allowed us to significantly improve classification performance compared to a processing chain that does not include a spatial filtering step, and to obtain outstanding performances with up to 98% of correct classification using two virtual electrodes. It should be noted that there was an important inter-subject variability, which may explain why the filtered ERPs present small variations with load when averaged across subjects.

This study paves the way to building better processing chains for mental state monitoring applications, such as e-learning. However, it should be noted that our mental workload estimation is only based on event-related potentials of task-related or task-relevant items. Therefore, although we achieved very high classification performances, this is a focused improvement, for applications in which the system knows and controls the visual (or auditory) display. Hence, it has low generalization capabilities. In order to progress towards efficient passive BCI systems that can generalize to any task, the next step is to evaluate how task-irrelevant probes can be used to estimate mental workload.

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