A Comparison of ERP Spatial Filtering Methods for Optimal Mental Workload Estimation

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***Abstract*— Mental workload estimation is of crucial interest for user adaptive interfaces and neuroergonomics. Its estimation can be performed using event-related potentials (ERPs) extracted from electroencephalographic recordings (EEG). Several ERP spatial filtering methods have been designed to enhance relevant EEG activity for active brain-computer interfaces. However, to our knowledge, they have not yet been used and compared for mental state monitoring purposes. This paper presents a thorough comparison of three ERP spatial filtering methods: principal component analysis (PCA), canonical correlation analysis (CCA) and the xDAWN algorithm. Those methods are compared in their performance to allow for an accurate classification of mental workload when applied in an otherwise similar processing chain. The data of 20 healthy participants that performed a memory task for 10 minutes each was used for classification. Two levels of mental workload were considered depending on the number of digits participants had to memorize (2/6). The highest performances were obtained using the CCA filtering and the xDAWN algorithm respectively with 98% and 97% of correct classification. Their performances were significantly higher than that obtained using the PCA filtering (88%).**

I. INTRODUCTION

Event-related potentials (ERPs) are electrical deflections (positive or negative) observed within scalp electroencephalography(EEG) data in response to the appearance of a given stimulus. This activity is a well-known marker of cognitive functions such as working memory load [1]. Manipulating memory load (e.g. number of items to keep in memory) is a way to modulate task difficulty, or more generally mental workload [2]. Nowadays, workload is a mental state currently under a lot of focus in the neuroergonomics area and the mental state monitoring research. This mental state is particularly relevant for implementing user adaptive interfaces and user monitoring devices for safe transportation [3]. Therefore, the use of such EEG markers for mental workload estimation should be evaluated.

In order to estimate a given mental state from ERPs, processing chains originally developed for active brain-computer interfaces (BCI) can be used. Those chains generally include pre-processing steps such as denoising and epoching, an extraction of the desired ERP with a baseline correction, and then a classification step with a validation method such as a 10-fold cross-validation. In order to enhance classification performance, several authors have used spatial filtering methods applied on the ERPs. Amongst those methods, there is the canonical correlation analysis (CCA) developed by Hotteling [4] and used by Spüler and collaborators to filter ERPs for active BCI applications [5]. Another interesting method is the xDAWN algorithm designed by Rivet and collaborators to enhance the signal on signal plus noise ratio for the P300 speller BCI application [6]. To our knowledge, ERP spatial filtering methods have never been directly compared for mental state monitoring applications such as mental workload estimation.

In the present study, we compare the usefulness of three spatial filtering methods for ERP-based mental workload estimation by means of the classification performance obtained with an otherwise similar processing chain.

II. METHODS

The three ERP spatial filtering methods tested and compared for mental workload estimation were the following: principal component analysis (PCA), canonical correlation analysis (CCA) and xDAWN algorithm. The comparison was also performed relative to a condition without spatial fitering (RAW). In this section, we detail the dataset, processing chains, spatial filtering methods and statistical analyses that we used for mental workload estimation.

A. Dataset

This research was promoted by the University Hospital of Grenoble, approved by the local French ethics committee of south-east France (ID number: 2012-A00826-37) and the French health safety agency (B120921-30).

Mental workload was manipulated using a modified Sternberg paradigm [7]. In 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 probe item flanked with question marks was presented (Fig. 1). The participants had to answer as quickly as possible whether the probe was present or not in the memorized list using a response box.

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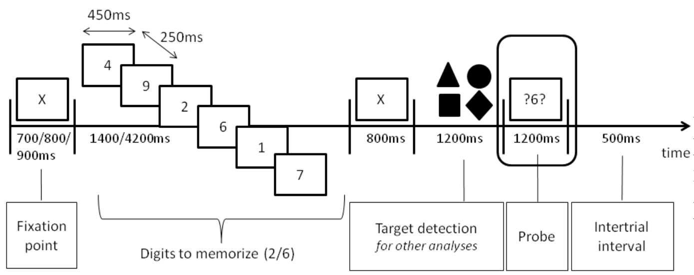

Fig. 1. Structure of a trial from the memory task performed by the participants. The circled segment corresponds to the analyzed window from which the evoked potential is extracted.

Two levels of workload were considered, i.e. 2 and 6 digits to memorize (low and high workload respectively). The task was performed for 10 minutes, which amounted to 40 trials per workload level. Trials of low and high workload were pseudo-randomly presented. Workload manipulation was confirmed thanks to behavioral measures. Participants were slower to respond and had a lower accuracy in high workload conditions than in low ones ($p < 0.001$).

Participant's EEG activity was recorded using a BrainAmp^{TM} system (Brain Products, Inc.) and an Acticap equipped with 32 Ag-AgCl active electrodes that were 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 for artefact rejection using two electrodes positioned at the eyes outer canthi, and two respectively above and below the left eye.

B. Processing chains & Analyses

In order to fairly compare the different spatial filtering methods, the same preprocessing was applied to the EEG dataset and the dimensionality of the feature vector was made identical in each condition. First, for each participant, the EEG dataset was band-pass filtered between 1 and 40 Hz and epoched with respect to the appearance of the probe item (see Fig. 1). Each 600 ms data epoch was re-referenced using a common average reference filter and denoised using the SOBI algorithm [8]. Each ERP was then decimated from 500 Hz to 100 Hz using a moving average filtering. Finally, each ERP was baseline corrected by subtracting to it the averaged voltage of the 200 ms that preceded the stimulus display. Next, a spatial filtering step was applied (two spatial filters, corresponding to the highest eigenvalues; optimal as shown in [9]).

Thus, each trial was associated with a feature vector of dimension 120x1 by concatenating the two spatially filtered waveforms. Note that the RAW condition extracted the EEG signals from electrodes Cz and POz, since central and parieto-occipital regions are very often cited as major sites for observing workload modulations due to visual stimulations [10], [11]. Then, a Fisher Linear Discriminant Analysis (FLDA) intra-subject classification step was performed, using a shrinkage estimation of the covariance matrices [12]. Lastly, a 10-fold cross-validation step was performed.

The classification performance obtained for each of the 4 chains (RAW, PCA, xDAWN, CCA) was statistically compared using a repeated measure ANOVA, a Tukey post-hoc test for multiple mean comparisons, and a single sample t-test to test the performances against chance level. The significance level was set to 0.05.

C. Spatial filtering methods

Let us denote by $\mathbf{X} \in R^{N_e \times N_s}$ the band-pass filtered EEG matrix, with N_e the number of EEG channels, and N_s the total number of samples. The sample covariance matrix is given by $\mathbf{\Sigma_x} = \frac{1}{N_s}\mathbf{x}\mathbf{x}^T$. The spatially filtered signal is given by $\mathbf{Z} = \mathbf{W}^T\mathbf{X}$.

1) PCA: Principal component analysis (PCA) performs a linear and orthogonal transformation to obtain uncorrelated components. The transformation matrix $\mathbf{W}$ is obtained by the eigenvalue decomposition (EVD) of the covariance matrix:

$$\mathbf{\Sigma_x} = \mathbf{U_x}\mathbf{\Lambda}\mathbf{U_x}^T$$

The eigenvalues, i.e. the diagonal elements of $\mathbf{\Lambda_x}$, are sorted in decreasing order and correspond to the variance of the filtered signals. By choosing $\mathbf{W} = \mathbf{U_x}$, it is readily seen that:

$$\mathbf{\Sigma_Z} = \mathbf{W}^T\mathbf{\Sigma_x}\mathbf{W} = \mathbf{\Lambda_x}$$

Sphering is obtained by the relation: $\mathbf{W} = \mathbf{U_X}\mathbf{\Lambda_X}^{-\frac{1}{2}}$.

Hence, $\mathbf{W}$ contains the orthogonal eigenvectors whose eigenvalues reflect the proportion of total variance of the signal contained in each one of them [13]. The components that contain the largest part of the total variance can therefore be selected to be used as filters onto the EEG signal.

2) xDAWN: The EEG generative model is given by:

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

The matrices $\mathbf{D}_1, \mathbf{D}_2 \in R^{M \times N_s}$ are binary Toeplitz sparse (M is the number of samples per ERP) and contain the stimulation events. The matrices $\mathbf{P}_1, \mathbf{P}_2 \in R^{N_e \times M}$ correspond to the stereotypical evoked response matrices and the matrix $\mathbf{N}$ describes an additional noise term.

In our model, $\mathbf{P}_1\mathbf{D}_1$ corresponds to the specific ERP responses for the high workload condition, whereas $\mathbf{P}_2\mathbf{D}_2$ corresponds to the common response for all conditions (low and high workload). The stereotypical responses contained within $\mathbf{P}$ are estimated by solving the following problem in the least squares sense:

$$\hat{\mathbf{P}} = \text{argmin}_{\mathbf{P}} \parallel \mathbf{X} - \mathbf{PD} \parallel_F^2$$

Next, the spatial filters are computed by maximizing the criterion:

$$\rho(\mathbf{w}) = \frac{\mathbf{w}^T \mathbf{\Sigma}_{\mathbf{x}_1} \mathbf{w}}{\mathbf{w}^T \mathbf{\Sigma}_{\mathbf{x}} \mathbf{w}}$$

where $\mathbf{X}_1 = \hat{\mathbf{P}}_1 \mathbf{D}_1$. The Rayleigh quotient is maximized by solving a generalized EVD problem. The xDAWN filters are thus designed to enhance the ratio between the signal and the signal plus noise ratio (SSNR).

3) CCA: As described by Spüler and collaborators [5], the canonical correlation analysis (CCA) is a multivariate statistical method that can be used to find linear transformations that maximize the correlation between two sets of data. The EEG generative model is similar to that of the xDAWN algorithm. However, $\hat{\mathbf{P}}_2 \mathbf{D}_2$ now corresponds to the specific ERP response for the low workload condition.

A possible manner to employ CCA for ERP spatial filtering and classification is to consider the EEG dataset $\mathbf{X}$ and the denoised dataset $\mathbf{X}_f = \hat{\mathbf{P}}\mathbf{D}$, which corresponds to the ERP answer averaged across trials. CCA aims at maximizing the correlation between both filtered signals $\mathbf{z}_i = \mathbf{w}_i^t \mathbf{X}$ and $\mathbf{z}_{f,i} = \mathbf{w}_{f,i}^t \mathbf{X}_f$.

III. RESULTS

A. ERPs

A significant decrease in amplitude was found at the group level for the N2 ERP component (negative deflection around 200 ms post-stimulation) at the Cz electrode site when workload increased ($p < .05$; Fig. 2).

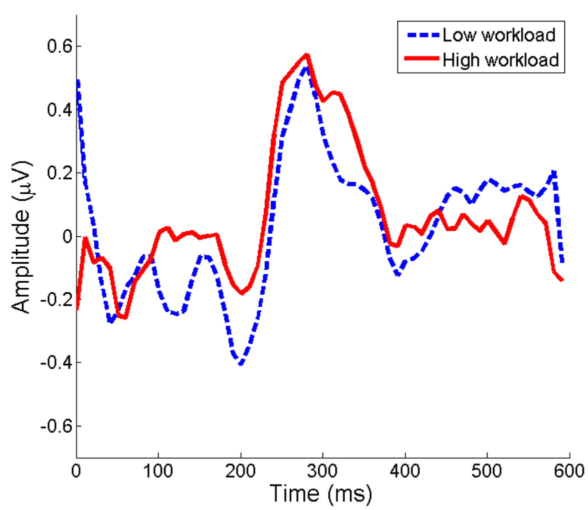

Fig. 2. Grand average ERP at the Cz electrode (across all participants).

B. Classification performance

The classification performance results are given by Fig. 3. Classification performance was significantly different from chance level only for the three chains that included a spatial filtering step ($p < 0.001$; RAW chain: $p = 0.65$). Moreover, classification performance was significantly different between the four processing chains ($F(3, 57) = 228.14, p < 0.001$). Both xDAWN (97%) and CCA (98%) gave significantly better results than PCA (88%), and all the chains that included a spatial filtering step gave significantly higher results than the RAW chain ($p < 0.001$). There was no significant difference in performance between the CCA and the xDAWN chains ($p = .99$).

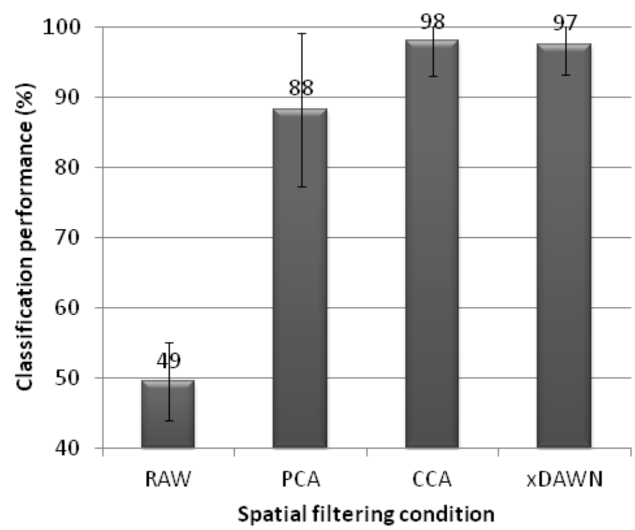

Fig. 3. Classification performance of the different processing chains depending on the applied spatial filtering method.

C. Spatial patterns

Fig. 4 gives the averaged spatial patterns across participants for the two filters of each spatial filtering method. For the 1st filter, the three methods enhanced the activity from occipital and fronto-central sites. However, for the 2nd filter the spatial patterns differed between methods. Indeed, the 2nd filter of the CCA and xDAWN methods enhanced the activity at the occipital and central sites, whereas the PCA method, that gave a lower performance than the previously mentionned methods, enhanced the activity from the temporal sites. The implication of the temporal sites by the PCA to estimate workload, especially during a visual task, was not appropriate, as reflected by the poorer performance obtained with this chain.

IV. CONCLUSION & OUTLOOK

This study intended to compare the usefulness of evoked potential spatial filtering methods for mental state monitoring, and more particularly for mental workload estimation. Data acquired while participants performed a memory task were used to extract the analyzed ERPs. At

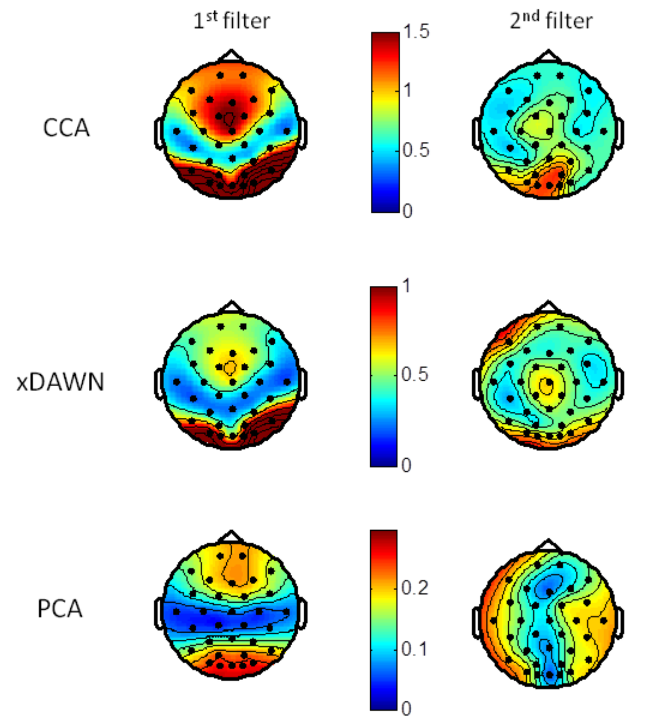

Fig. 4. Spatial patterns of the first 2 filters for each spatial filtering method.

the neurophysiological level, a workload effect was found across participants on the N2 component. Its amplitude decreased when workload increased, in accordance with the literature [10], [14], [15]. As regards mental workload estimation, the same processing chain was used, but for the spatial filtering step. Indeed, the chains either included a PCA, CCA or xDAWN filtering step, or no filtering step at all. A filtering step was necessary in order to obtain classification performances significantly higher than chance level. Also, the best performance was achieved using the CCA or the xDAWN filtering methods, with as high as 98% of correct classification. The fact that the PCA method gave lower results than the other two methods could be explained by its underlying assumption that sources are orthogonal - as reflected by the obtained spatial patterns-, which is not true for electroencephalographic signals. However, in any case, the results obtained using any spatial filtering step were higher than that obtained by Brouwer and collaborators [16]. Indeed, they reached only about 64% using n-back evoked potentials of 1 s extracted from 7 electrodes in a single-trial design. Therefore, a spatial filtering step seems necessary to greatly increase mental workload estimation based on single-trial ERPs.

The optimal performances that we obtained in a single-trial fashion indicate that workload estimation using evoked potentials is more than feasible and should be considered for mental state monitoring system implementation. However, in this study we used the evoked potentials elicited by a stimulus linked to the task at hand. In order to go further in the applicability of this estimation method, future work should evaluate the use of task-independent stimuli, and even ignored stimuli, such as ignored auditory probes. Indeed, those stimuli have been shown to induce modulations in evoked potentials with increasing workload [14], [17]. Hence, the use of such probes would be less intrusive and would allow for a quick although non continuous mental state assessment.

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