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Subspace estimation approach to P300 detection and application to Brain-Computer Interface

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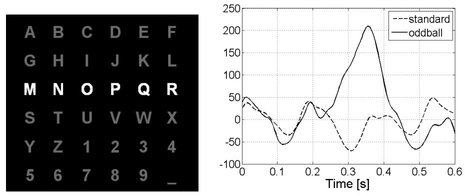
Abstract— **Brain-computer interface (BCI) is a system for direct communication between brain and computer. In this work, a new unsupervised algorithm is introduced for P300 subspace estimation: the raw EEG are thus enhanced by projection on the estimated subspace. Moreover a simple scheme to detect the P300 potentials in the human EEG by dimension reduction and linear support vector machine (SVM) is proposed to build a BCI based on the P300 speller. The proposed algorithm is finally tested with dataset from the BCI Competition 2003 and gives results that compare favourably to the state of the art.**

I. INTRODUCTION

Brain-Computer Interfaces (BCI) enable direct communication between the user's brain and a computer by analysing electroencephalographic (EEG) activities that reflect the brain functions [1], [2]. Such kind of human-computer interfaces, that provides a new non-muscular powerful channel for communicating with the external world, is suitable for people that are incapable of any motor functions (e.g. people with severe neuromuscular disorders or 'locked in' people). Present-day BCIs determine the intent of the user from different electrophysiological signals : for instance, the user may control some brain waves (e.g. mu or beta rhythms) or the BCI may exploit natural responses of the brain to external stimuli (e.g. event-related potentials) [1].

The BCI problem we are addressing in this paper concerns the P300 speller [3], [4]: it enables people to write text on a computer. It is based on natural responses of the brain to external visual stimuli (oddball paradigm). The task is thus to discriminate between epochs containing a P300 potential which is evoked by the target stimulus from epochs associated with the non-target stimuli. Unfortunately, the signal-to-noise ratio (SNR) of EEG signals is very low, and moreover the recorded EEG signals may also contained muscular and/or ocular artefacts. Several methods, based on independent component analysis (ICA), were thus proposed to enhance the SNR and to remove the artefacts [5], [6]. However, the major drawback of such methods is that they are not specifically designed to separate brain waves and they are supervised. Indeed, after the decomposition in independent components (IC) it is necessary to select (manually or thanks to spatio-temporal prior) the ICs which contained the evoked potentials.

In this paper, we propose a new unsupervised algorithm to automatically estimate P300 subspace from raw EEG signals. The aim is to provide a new method so that the spelling debit is increased. This paper is organized as follows. Section II describes the P300 subspace estimation and the BCI classification problem. Section III presents the results that have been achieved whereas Section IV concludes the paper with comments and perspective on the work.



(a) (b)

Fig. 1. Brain-Computer Interface "*P300 speller*". Fig. 1(a): screen display as was shown to the subjects with an highlighted row. Fig. 1(b): time course of the actual average signal waveforms at C_z.

II. METHODOLOGY

The aim of this study is to provide a simple and unsupervised estimation of the P300 subspace so that the classification between target/non-target epochs is simplified which thus leads to a faster spelling device.

A. P300 speller Brain-Computer Interface

The BCI addressed in this paper is the P300-speller introduced by Farwell and Donchin [3]. It enables users to spell a text: a 6×6 matrix, that includes all the alphabet letters as well as other symbols, was presented to the user on a computer screen (Fig. 1(a)). A sequence is thus defined as the intensification of each of the 6 rows and of the 6 columns in a random order. To spell a character, the users had to mentally count the number of times the letter/symbol, they wish to communicate, is intensified. In response to this counting, a P300 evoked potential was elicited in the brain (*i.e.* a positive deviation around 300ms after the stimulus). The desired character hence appears on 2 out of the 12 intensifications in a sequence, since a character is defined as the intersection of a given row and a given column. The task is thus to detect the oddball stimuli (row/column intensifications) which lead to a P300 evoked potential (Fig. 1(b)). To produce a more robust BCI, each character was spelt several consecutive times. However, this repetition decreases the number of characters spelt per minute: e.g. with 15 repetitions, only 2 characters were spelt per minute [3], [4].

The aim of the proposed method is thus to correctly predict a character by as low as possible sequence repetitions leading

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to increase the information rate.

B. P300 subspace estimation

The raw EEG recorded from the user's scalp not only contain the desired P300 evoked potentials but also ongoing activity of the brain and muscular and/or ocular artefacts. As a result, the SNR is very low and the classification task (*i.e.* the character prediction) is not easy. We thus proposed to enhance the P300 potentials by projecting the raw recorded EEG on the P300 subspace (*i.e.* the subspace which contains most of the P300 potentials) before the classification.

To estimate P300 subspace, a learning database is used. It consists in a database for which the spelt characters are known as well as the order of rows/columns intensifications and the corresponding timecodes (*i.e.* beginning time of illumination).

Let $\phi_1(t)$ denote a typical time course of a P300 potential, which is called a kernel. Using the learning database (for which the oddball stimuli were known), it is possible to define a reference signal $r_1(t)$ to the P300 potentials time course by

$$r_1(t) = \sum_{j=1}^{J} \alpha_j \ \phi_1(t) * \delta(t - \tau_j), \tag{1}$$

where $\delta(t)$ is the Dirac delta function, τ_j the (known) times of oddball stimuli which elicited a P300 potential in the brain, α_j is a scale factor, J the number of oddball stimuli and $*$ is the convolution product.

Let $\mathbf{x}(t) \in \mathbb{R}^{N_s}$ denote the observations vector at time index t (N_s is the number of sensors). The aim of the P300 subspace estimation is to estimate a vector $\hat{\mathbf{b}}$ such that

$$\left(\hat{\mathbf{b}}, \hat{\alpha}\right) = \arg \min_{\substack{(\mathbf{b},\,\alpha) \\ \|\mathbf{b}^T \mathbf{x}(t)\|_2 = 1 \\ \|r_1(t)\|_2 = 1}} \sum_{t=0}^{T-1} \left| \mathbf{b}^T \mathbf{x}(t) - r_1(t) \right|^2, \tag{2}$$

where $.^T$ is the transpose operator. $\alpha = [\alpha_1, \cdots, \alpha_J]^T$ is an unknown hyper-parameter which models the possibility that distinct P300 potentials may have different amplitudes. Using basic algebra manipulations, criterion (2) can be also expressed as

$$\left(\hat{\mathbf{b}}, \hat{\alpha}\right) = \arg \min_{\substack{(\mathbf{b},\,\alpha) \\ \|X\,\mathbf{b}\|_2 = \|M\,\alpha\|_2 = 1}} \left\| X\,\mathbf{b} - M\,\alpha \right\|_2^2, \tag{3}$$

where $M \in \mathbb{R}^{T \times J}$ whose j-th column entries are $\phi_1(t) * \delta(t - \tau_j)$ for all $t \in \{0, \cdots, T-1\}$, and $X = [\mathbf{x}(0), \cdots, \mathbf{x}(T-1)]^T \in \mathbb{R}^{T \times N_s}$.

Let $\mathcal{E}_X$ (resp. $\mathcal{E}_M$) denote the space spanned by X (resp. M), and let Q_X (resp. Q_M) denote an orthonormal basis of $\mathcal{E}_X$ (resp. $\mathcal{E}_M$). The solution of problem (3) is thus given by the couple of singular vectors $(\hat{\mathbf{b}}, \hat{\alpha})$ associated with the largest singular value of $Q_X^T\, Q_M$. However, kernel $\phi_1(t)$ used to generate matrix M is unfortunately unknown. To overcome this difficulty, a recursive scheme to estimate the best kernel $\phi_1(t)$ is proposed.

Let $\phi_1^{(k)}(t)$ denote the estimation of kernel $\phi_1(t)$ at step k and let $M^{(k)}$ denote the matrix M generated thanks to the estimation of kernel $\phi_1(t)$ at the previous step. The j-th column entries of $M^{(k)}$ is thus given by $\phi_1^{(k-1)}(t) * \delta(t - \tau_j)$ for all $t \in \{0, \cdots, T-1\}$. Solving (3) provides a couple $\left(\mathbf{b}^{(k)}, \alpha^{(k)}\right)$ which leads to $s_1^{(k)}(t) = \mathbf{b}^{(k)}\,\mathbf{x}(t)$ and to $r_1^{(k)}(t) = M^{(k)}\,\alpha^{(k)}$. Signal $s_1^{(k)}(t)$ is then epoched to update $\phi_1^{(k)}(t)$: $\forall\, j \in \{1, \cdots, J\}$

$$f_j^{(k)}(t) = \left(s_1^{(k)}(t) \times \Pi_{T_{300}}(t - \tau_j) \right) * \delta(t + \tau_j), \tag{4}$$

where $\Pi_{T_{300}}(t)$ is the boxcar function equal to 1 on its support $[0, T_{300}]$ and equal to 0 elsewhere (typically $T_{300} =$ 600ms). $\phi_1^{(k)}(t)$ is finally defined as the mean of all P300 epochs $f_j^{(k)}(t)$:

$$\phi_1^{(k)} = \frac{1}{J} \sum_{j=1}^{J} \mathbf{f}_j^{(k)} \tag{5}$$

where $\phi_1^{(k)} = [\phi_1^{(k)}(0), \cdots, \phi_1^{(k)}(T_{300} - 1)]^T$ and $\mathbf{f}_j^{(k)} = [f_j^{(k)}(0), \cdots, f_j^{(k)}(T_{300} - 1)]^T$. When convergence is reached, this recursive scheme leads to $\hat{\mathbf{b}} = \mathbf{b}^{(k)}$ which is the main component of P300 subspace.

To estimate P300 subspace of dimension I higher than one, an iterative algorithm is proposed. Let $\mathbf{b}_i$ denote the i-th estimated component of P300 subspace and let V_i be the space spanned by $\{\mathbf{b}_1, \cdots, \mathbf{b}_i\}$. To estimate $\mathbf{b}_{i+1}$, the recursive scheme described above is applied on $\mathbf{x}_{i+1}(t)$, where $\mathbf{x}_{i+1}(t)$ is the observation vector $\mathbf{x}(t)$ projected on $V_i^{\perp}$, with $V_i^{\perp}$ the orthogonal space of V_i (note that $\mathcal{E}_X = V_i \overset{\perp}{\bigoplus} V_i^{\perp}$).

The iterative algorithm to estimate by deflation P300 subspace of dimension I is finally summarized in Algorithm 1.

Algorithm 1 Iterative estimation of P300 subspace.

1: $\mathbf{x}_1(t) = \mathbf{x}(t)$, $X_1 = X$
2: **for** $i = 1$ to I **do**
3:   compute Q_{X_i} orthonormal base of $\mathcal{E}_{X_i}$
4:   $k = 0$, initialisation of $\phi_i^{(0)}(t)$ by an arbitrary form
5:   **while** no convergence reached **do**
6:     $k \leftarrow k + 1$
7:     compute $M^{(k)}$ thanks to $\phi_i^{(k-1)}(t)$
8:     compute $Q_{M^{(k)}}$ orthonormal base of $\mathcal{E}_{M^{(k)}}$
9:     perform singular value decomposition of $Q_{X_i}^T\, Q_{M^{(k)}} \Longrightarrow (\mathbf{b}^{(k)}, \alpha^{(k)})$
10:     $s_i^{(k)}(t) = \mathbf{b}^{(k)^T} \mathbf{x}_i(t)$
11:     epoch $s_i^{(k)}(t) \Longrightarrow \mathbf{f}_j^{(k)}$ for $j \in \{1, \cdots, J\}$ (4)
12:     update $\phi_i^{(k)} = \frac{1}{J} \sum_{j=1}^{J} \mathbf{f}_j^{(k)}$
13:   **end while**
14:   $\mathbf{b}_i = \mathbf{b}^{(k)}$, $\phi_i(t) = \phi_i^{(k)}(t)$
15:   project $\mathbf{x}_i(t)$ on $V_i^{\perp} \Longrightarrow x_{i+1}(t),\ X_{i+1}$
16: **end for**

We observed on numerous experiments on real data that the recursive scheme (steps 5 to 13) typically converges to a stable solution independently of the initialisation.

C. BCI classification

In the P300 speller BCI problem, the spelt character is identified by the detection of a P300 evoked potential related to a given row and to a given column illuminations for each sequence. Among the proposed classifiers for BCIs, linear support vector machines (SVM) [7] are chosen since they proved to be efficient [8].

However, unlike the previously SVM based classifiers (e.g. [8]) whose input vector are concatenation of time courses of P300 potentials recorded on different EEG channels, the proposed classifier operates on a new representation vector of the data described below.

For each sequence, composed of a total of 12 intensifications (6 rows and 6 columns), and for each dimension i of the estimated P300 subspace (estimated by Algorithm 1 of Section II-B), let $\alpha(i) = [\alpha_1(i), \cdots, \alpha_{12}(i)]^T$ be the vector of amplitude coefficients $\alpha_j(i)$ between $\mathbf{b}_i\, \mathbf{x}(t)$ and $\phi_i(t) * \delta(t - \theta_j)$, with θ_j the timecode of the j-th illumination. $\mathbf{b}_i$ and $\phi_i(t)$ are the i-th spatial filter and the i-th kernel provided by the proposed P300 subspace estimation respectively. $\alpha(i)$ is thus obtained by

$$\hat{\alpha}(i) = \arg\min_{\alpha(i)} \left\| X\, \mathbf{b}_i - M_i\, \alpha(i) \right\|_2^2, \qquad (6)$$

where $X = [\mathbf{x}(0), \cdots, \mathbf{x}(T_s - 1)]^T$ (T_s is the time length of a sequence). $M_i \in \mathbb{R}^{T_s \times 12}$ denotes the model matrix whose j-th column entries are given by $\phi_i(t) * \delta(t - \theta_j)$ for all $t \in \{0, \cdots, T_s - 1\}$. $\alpha(i)$ is finally estimated by

$$\hat{\alpha}(i) = \left(M_i^T\, M_i\right)^{-1} M_i\, \left(X\, \mathbf{b}_i\right). \qquad (7)$$

Parameter vector $\mathbf{p}_j \in \mathbb{R}^I$ corresponding to the j-th illumination is then given by the concatenation of I amplitude factors $\alpha_j(i)$, $1 \leq i \leq I$: $\mathbf{p}_j = [\alpha_j(1), \cdots, \alpha_j(I)]^T$. The main advantage of this new parametrisation if that each intensification is defined by a vector whose length is I unlike a time course based parametrisation which requires a longer parametrisation vector.

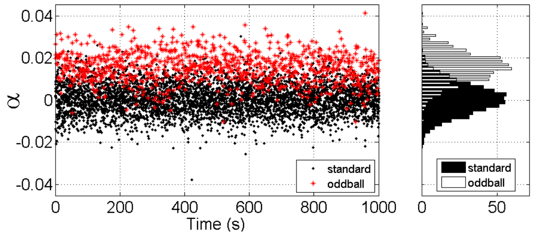
Let $h(\mathbf{p}_{rc})$ denote the score of a given row or column rc provided by the output of the SVM for a given sequence of all rows and columns matrix illumination. The overall score $H_{rc}(k)$ of row/column rc after k repetitions is thus given by

$$H_{rc}(k) = H_{rc}(k-1) + h(\mathbf{p}_{rc}), \qquad (8)$$

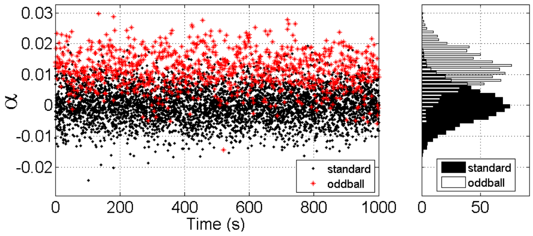
with $H_{rc}(0) = 0$. After the k-th repetition, the recognized character is the one with maximal row and column scores.

III. RESULTS

The proposed methodology, to estimate P300 subspace (Section II-B) and to recognize the spelt character (Section II-C), is applied on the data from the BCI 2003 competition dataset [9] which have been provided by the Wadsworth Center [10]. The data correspond to 64 EEG channels sampled at 240Hz. The raw EEG were first filtered by a 4-order bandpass filter with cut-off frequencies of 1Hz and 20Hz. Several experiments have been carried out to analyse the benefit of our approach.



(a) Coefficients $\alpha(i)$ associated with the first component of P300 subspace ($i = 1$).



(b) Coefficients $\alpha(i)$ associated with the second component of P300 subspace ($i = 2$).

Fig. 2. Distribution of amplitude coefficient vector $\alpha(i)$ (7) associated with the two first components of P300 subspace ($i = 1$ or 2). The left figures show coefficients $\alpha(i)$ for spelt characters (red crosses) and for non-spelt characters (black points). The right figures show the histograms of $\alpha(i)$ corresponding to spelt/non-spelt characters.

A. P300 subspace estimation

In a first experiment (Fig. 2), the P300 subspace estimation (Section II-B) was applied on the training database containing 39 characters. It provides I spatial patterns associated with I temporal kernels $\{(\mathbf{b}_i, \phi_i(t))\}_{1 \leq i \leq I}$. These I couples were then used to estimated coefficients $\{\alpha(i)\}_{1 \leq i \leq I}$ (7) for the 31 spelt characters from the testing database. Coefficients $\alpha(i)$ are plotted in Fig. 2 in a concatenated form (*i.e.* concatenation of coefficients $\alpha(i)$ obtained for each of the 31 characters). As expected, one can see that coefficients $\alpha(i)$ are larger when they correspond to target intensifications (red crosses, white histogram) than when they correspond to standard illuminations (black points, black histogram). This experiment shows that parameter vector $\mathbf{p}_j = [\alpha_j(1), \cdots, \alpha_j(I)]^T$ could be used to the prediction of spelt characters. However, one can see that there is an overlap between the distribution of coefficients $\alpha(i)$ corresponding to spelt characters (white histograms) and the distribution of coefficients $\alpha(i)$ associated with non-spelt characters (black histograms). This stresses that a single sequence is not sufficient to perfectly predict the spelt character: as a consequence, several sequences for each spelt characters are necessary to increase the performance.

B. BCI classification

In a second experiment, we compare the prediction results of the proposed method to those obtained by different methods. The results of the classification are summarized in Tab. I, where are given the number of misspellings in the

TABLE I

NUMBER OF MISSPELLINGS IN THE TEST WORDS (31 CHARACTERS) WITH RESPECT TO THE NUMBER OF SEQUENCES AND TO THE ALGORITHM.

	Number of sequences						
	1	2	3	4	5	10	15
10 preselected channels[1]	22	17	12	10	5	4	2
10 preselected channels[2]	16	14	11	4	4	1	0
optimal relevant channels and 1 SVM per word [8]	4	2	1	0	0	0	0
First dimension of P300 subspace (estimated by algorithm 1)	8	8	5	4	3	1	0
2 first dimensions of P300 subspace (estimated by algorithm 1)	7	7	2	2	0	0	0
3 first dimensions of P300 subspace (estimated by algorithm 1)	7	5	1	0	0	0	0
4 first dimensions of P300 subspace (estimated by algorithm 1)	7	5	1	0	1	0	0
5 first dimensions of P300 subspace (estimated by algorithm 1)	8	5	1	0	1	0	0
10 first dimensions of P300 subspace (estimated by algorithm 1)	10	7	3	0	1	0	0

test words (corresponding to a total amount of 31 characters) with respect to the number of sequences and to the algorithm.

In the two first tests, two sets of 10 channels are manually preselected. In each case, the classifier is a single linear SVM whose input parameter vector is the concatenation of 667ms time courses corresponding to the preselected channels. One can see the need of an appropriate channels selection: a wrong selection of channels dramatically decreases the performance as shown in table. I (two first rows).

The proposed method was then applied to estimate the P300 subspace (Section III-A), and a single linear SVM was trained on parameter $\mathbf{p}_j$ (Section II-C). One can see that the proposed method using only the first component of P300 subspace outperforms the use of 10 preselected channels. This highlights the benefit to project the raw EEG on the P300 subspace before the word prediction. Note that if only the first component of the P300 subspace is used, the parameter vector $\mathbf{p}_j$ reduces to single scalar $\alpha_j(1)$ as shown in Fig. 2(a) and the linear SVM only selects the row and the column with largest $\alpha_j(1)$. Moreover, only a few number of P300 subspace components are needed to provide good performance: indeed with the three first components of P300 subspace, all the words in the test set can be recognized correctly with only 4 sequences. Note that using more than 3 components slightly increases the number of misspellings.

Finally, the method proposed by Rakotomamonjy *et al.* [8] sightly outperforms the proposed method. However, the method presented in [8] uses a more complicated classifier to take into account the possible variabilities in EEG records: it is based on as many SVMs as words in the training database (in this case it thus uses 11 different SVMs) and for each SVM a selection of channels is applied.

IV. CONCLUSION

The proposed unsupervised method provides a simple and dedicated scheme to estimate P300 subspace. Indeed, given the time indexes of illuminations, the proposed algorithm 1 iteratively estimates the main components of P300 subspace. Moreover, the proposed scheme significantly reduces the dimension of the parameter vector used to the prediction word. The proposed approach has been shown to be suitable for a BCI and gives results that compare favourably to the state of the art. Unlike the method presented in [8] which only selects channels (0 or 1 weightings) that are important for the detection of event-related potentials, the proposed algorithm also automatically and optimally weights all the channels according to their relative relevance.

To further improve the classification performance, it can be interesting to use several linear SVMs which allow to deal with the variability of EEG responses as in [8].

[1] The 10 preselected channels are: $\mathrm{F_{PZ}}$, $\mathrm{F_3}$, $\mathrm{F_z}$, $\mathrm{F_4}$, $\mathrm{C_3}$, $\mathrm{C_z}$, $\mathrm{C_4}$, $\mathrm{P_3}$, $\mathrm{P_z}$, $\mathrm{P_4}$.

[2] The 10 preselected channels are: $\mathrm{F_z}$, $\mathrm{C_z}$, $\mathrm{P_z}$, $\mathrm{O_z}$, $\mathrm{C_3}$, $\mathrm{C_4}$, $\mathrm{P_3}$, $\mathrm{P_4}$, $\mathrm{P_{O7}}$, $\mathrm{P_{O8}}$.

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