Sensor selection for P300 speller brain computer interface

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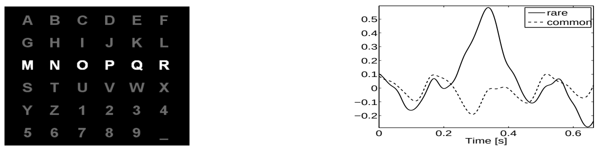
Abstract. Brain-computer interfaces (BCI) are communication system that use brain activities to control a device. The BCI studied is based on the P300 speller [1]. A new algorithm to select relevant sensors is proposed: it is based on a previous proposed algorithm [2] used to enhance P300 potentials by spatial filters. Data recorded on three subjects were used to evaluate the proposed selection method: it is shown to be efficient and to compare favourably with a reference method [3].

1 Introduction

Brain computer interfaces (BCI) are devices which enable a direct communication between the user's brain and a computer [4] by exploiting electroencephalographic (EEG) activities and are thus suitable for people who are incapable of any motor functions (e.g., people with severe neuromuscular disorders or "locked in" people). The BCI studied in this paper is the P300 speller [1] which enables people to spell a text or symbols such as numbers on a computer. It is based on the odd-ball paradigm. 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)). To spell a character, the users had to mentally count the number of times the letter/symbol, they wish to communicate, is intensified. As a result of the attentional focus which is enhanced by mental counting, a P300 evoked potential was elicited in the brain (i.e. a positive deviation around 300ms after the stimulus, 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 [1].

The task of the BCI is to discriminate target/non-target stimuli thanks to the detection of the evoked potentials. Unfortunately, the signal-to-noise ratio (SNR) of EEG signals is very low, and moreover the recorded EEG signals may also contain some muscular and/or ocular artefacts. Several methods based on spatial filtering were proposed to enhance the evoked potentials (e.g., among

*This work was partially funded by the BQR MoDyC (Grenoble INP) and by the ANR Open-ViBE (Grant ANR05RNTL016).



(a) (b) P300 evoked potentials

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.

many others [5, 6, 2]) before the classifier. These studies show that less training symbols (i.e. pre-determined letters) are required to obtain the same classification accuracy than classical methods which do not enhance P300 potentials by spatial filtering: as a consequence the ergonomics is improved since the training phase is speed up. Moreover to improve any longer the BCI ergonomics the need of reducing the number of electrodes is clear. Nevertheless, only few studies focus on an efficient sensors selection to choose the most relevant channels. Some of these studies try several predefined sets of sensors (e.g., [7, 8]) on classification accuracy, while only few studies (e.g., [3]) try to select sensors by blind methods, i.e. without predefined sets of sensors. The major drawback of [3] is that it is computationally expensive since it is based on a K-fold cross validation and it requires a large number of training symbols. The aim of this study is to provide an efficient method to automatically select revelant sensors for the P300 speller with a few number of training symbols.

This paper is organised as follows. Section 2 describes the sensors selection method, while numerical results are provided in Section 3. Section 4 concludes the paper with comments and perspectives.

2 Sensor selection

The aim of the proposed method is i) to correctly predict a character with as low as possible sequence repetitions leading to increase the information rate, and ii) to automatically select the most relevant sensors with as few training data as possible with a low computational cost method.

2.1 Enhancement of P300 potentials

In this section, the method proposed in [2] is briefly recalled. It is based on two main ideas: i) there exists a typical response synchronised with the target stimuli superimposed with an evoked response by all the stimuli (target plus non-target), ii) the evoked response to target stimuli might be enhanced by a spatial filtering.

Based on the first assumption, one can model the recorded signals X by

$$X = D_1\, A_1 + D_2\, A_2 + N, \tag{1}$$

where $X \in \mathbb{R}^{N_t \times N_s}$, N_t and N_s are the number of temporal samples and the number of sensors, respectively. $D_1 \in \mathbb{R}^{N_t \times N_1}$ (resp. $D_2 \in \mathbb{R}^{N_t \times N_2}$) is a Toeplitz matrix whose first column elements are all zeros excepted those corresponding to target (resp. all) stimuli onsets. $A_1 \in \mathbb{R}^{N_1 \times N_s}$ and $A_2^{N_2 \times N_s}$ are the evoked responses to target stimuli and to all stimuli, respectively. N_1 and N_2 are the samples number of target and superimposed evoked potentials, respectively. Finally, $N \in \mathbb{R}^{N_t \times N_s}$ is the residual noise composed of the going brain activity which is not related to the stimuli and of artefacts.

The second idea leads to estimate spatial filters $U_1 \in \mathbb{R}^{N_s \times N_f}$ so that the signal to signal-plus-noise ratio (SSNR) of enhanced signals $D_1 A_1 U_1$ is maximised:

$$\hat{U}_1 = \arg\max_{U_1} \frac{\mathrm{Tr}\big(U_1^T \hat{A}_1^T D_1^T D_1 \hat{A}_1 U_1\big)}{\mathrm{Tr}\big(U_1^T X^T X U_1\big)}. \tag{2}$$

N_f is the number of spatial filters, and $\hat{A}_1$ is the least mean square estimation of A_1 (1). In [2], it was shown that spatial filters U_1 can be estimated thanks to a singular value decomposition (SVD). Moreover, the singular values correspond to the SSNRs of enhanced signals.

2.2 Sensor selection procedure

The algorithm to adaptively select relevant sensors is based on a recursive sensor elimination (i.e. backward elimination). At each iteration of the algorithm, each of the N remaining sensors is dropped one by one, the subsets of $N-1$ remaining sensors are then tested leading thus to N performance scores. Finally by choosing the best subset with the highest score, the worst sensor is eliminated. This iteration procedure is further continued until all the sensors are eliminated leadings thus to rank the relevance of each channel.

Classical methods often use classification accuracy as performance score: for each iteration and each subset, a classifier is trained and the performance score is the classification accuracy achieved with a test database (i.e. different data than those used to train the classifier) to avoid over-fitting of the classifier. The major drawback of these method is that they need a lot of data to train and to test the classifiers. As a consequence, the training phase is quite long. To overcome this problem, we propose to use a new and possibly simpler performance score: the largest signal to signal-plus-noise ratio achieved by the proposed method to enhance P300 potentials (Section 2.1) which corresponds to the largest singular value. Indeed, it seems rational that the better the SSNRs is the better the classification accuracy is. The proposed method has the main advantage that the same criterion is used i) to estimate spatial filters which enhance P300 potentials and ii) to select relevant sensors with a low computational cost.

3 Experimental results

3.1 Data acquisition, pre-processing and BCI classification

Three healthy male subjects, without previous experience with the P300 speller paradigm, participated voluntarily in the experiment. EEG activity was recorded with a BrainAmp amplifier (BrainProduct GmBH, Munich), from 29 Ag/AgCl scalp electrodes placed at standard positions of an extended 10-10 international system referenced to the nose and grounded to the forehead. The EEG was collected and stored using the BCI2000 system with P300 speller scenario [9]. Subjects were asked to focus on the current symbol (which was shown after the word in parentheses) and to mentally count the number of times this letter was intensified. The interstimulus interval is of 180ms: 100ms of row/column intensification and 80ms of delay between two consecutive intensifications. For each symbol, the 12 columns and rows were intensified 15 times. There was a 2.5s period between each character of a run. In total there were 75, 65 and 68 symbols for the first, second and third subject, respectively.

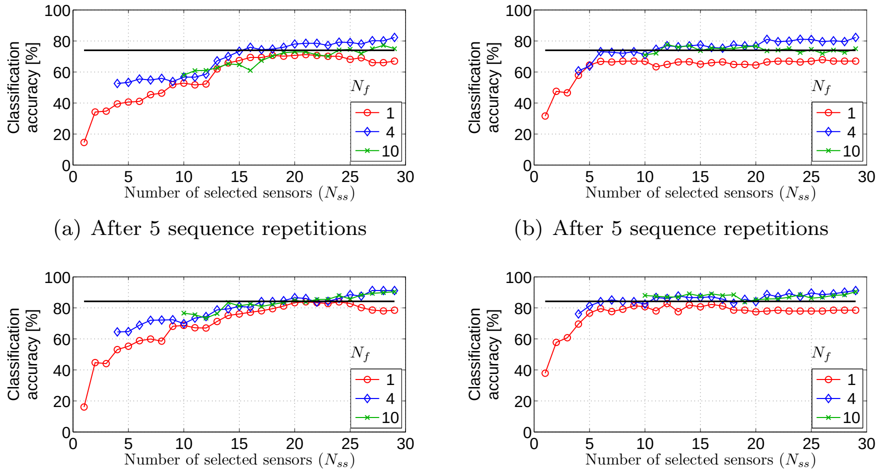
The EEG signals are sampled at 500Hz. Before estimating the spatial filters by the proposed method, the following pre-processing stages are applied. The data are first filtered by a fourth order forward-backward Butterwoth bandpass filter. Cut-off frequencies are set to 1Hz and 20Hz. For each sensor, the bandpass filtered signals were then normalised so that they had a zero mean value and a standard deviation equal to one. The temporal lengths of the synchronised responses A_1 and A_2 were chosen equal to one second.

Among the proposed classifiers for BCIs, Bayesian linear discriminant analysis (BLDA) [7] is chosen since it proved to be efficient and was fully automatic (i.e. no hyperparameters to adjust) [7]. It aims at finding a discriminant vector $\mathbf{w}$ such that $\mathbf{w}^T\mathbf{p}$ is as closed as possible to the class t associated with the corresponding feature vector $\mathbf{p}$ obtained from the concatenation of time-course samples of enhanced signals. This discriminant vector $\mathbf{w}$ is thus estimated from the set of couples $\{\mathbf{p}_j, t_j\}_{1\leq j\leq N_c}$ obtained from the N_c symbols of the training database.

3.2 Sensor selection results

This paragraph presents the results (Fig. 2) achieved using the proposed methodology. After selecting the relevant sensors, the proposed method to enhance P300 potentials [2] is applied before using the BLDA classifier. In each experiment only 5 symbols are used as training database, i.e. to select the most relevant sensors (Section 2.2), to estimate spatial filters U_1 (2) and to train classifier [7]. Two methods to select channels are compared: i) the performance score function is the classification accuracy (i.e. 'reference' method, Fig. 2(a) and 2(c)) and ii) the performance score function is the SSNR (i.e. proposed method, Fig. 2(b) and 2(d)). Fig. 2 shows the average classification accuracy (CA) achieved for the three subjects.

As one can see, the more sequence repetitions are, the better the classification accuracy is: the CA with 10 sequence repetitions (Fig. 2(c) and 2(d)) is better than with 5 sequence repetitions (Fig. 2(a) and 2(b)). The same positive correlation is observed with respect to the number of selected sensors: the more sensors are, the better the classification accuracy is. As already noticed in [2], only a few number of spatial filters ($N_f = 4$) is necessary to improve the CA:



(a) After 5 sequence repetitions (b) After 5 sequence repetitions

(c) After 10 sequence repetitions (d) After 10 sequence repetitions

Fig. 2: Sensor selection: classification accuracy versus the number of selected sensors for different configurations, legend refers to the number of spatial filters N_f (2). Fig. 2(a) and 2(c) (resp. 2(b) and 2(d)) refer to the reference method (resp. proposed method). Horizontal black line corresponds to classification accuracy achieved all sensors and without spatial filtering.

using more spatial filters (e.g., $N_f = 10$) does not improve the performance. Note that with all the sensors ($N_{ss} = 29$) using four spatial filters improves the CA (blue curves) compared with no spatial filtering (black lines). Moreover, it is important to highlight that the proposed method to select sensors is very efficient (Fig. 2(b) and 2(d)). Indeed, with only six sensors ($N_{ss} = 6$) and four spatial filters ($N_f = 4$) the CA is typically the same than with all sensors ($N_{ss} = 29$) and no spatial filtering (black line). Note that many more than six sensors ($N_{ss} \simeq 21$) are needed to significantly improve the performance (with $N_f = 4$). Finally, one can see that, with few training data, the proposed method (based on SSNR) to automatically select the relevant sensors is more efficient than the reference one (based on CA). Indeed, the six most significant sensors selected by the reference method are less accurate than the six most relevant sensors selected by the proposed method as shown by the CA which is smaller with the reference method (Fig. 2(a) and 2(c)) than with the proposed method (Fig. 2(b) and 2(d)). Moreover, with the reference method, at least 15 sensors are necessary to achieve the same CA than without sensor selection, while only 6 sensors are needed with the proposed selection method.

4 Conclusion and perspectives

In this paper, an original and efficient method to automatically select relevant sensors for the P300 speller BCI is proposed. This method has been shown to improve the relevance of selected channels compared to a reference method especially when few training data are available. As a consequence, the P300 speller ergonomics is improved since less sensors are necessary. The presented preliminary results are promising. Of course more in-depth validations are necessary towards more inter and intra subjects results. Future research will for instance investigate the variability of the selected sensors for one subjet over different sessions and days.

References

[1] L. A. Farwell and E. Donchin. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology*, 70(6):510–523, 1988.

[2] B. Rivet, A. Souloumiac, G. Gibert, and V. Attina. "P300 speller" Brain-Computer Interface: Enhancement of P300 evoked potential by spatial filters. In *Proc. EUSIPCO*, Lausanne, Switzerland, August 2008.

[3] A. Rakotomamonjy and V. Guigue. BCI Competition III: Dataset II- Ensemble of SVMs for BCI P300 Speller. *IEEE Transactions on Biomedical Engineering*, 55(3):1147–1154, 2008.

[4] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6):767–791, 2002.

[5] N. Xu, X. Gao, B. Hong, X. Miao, S. Gao, and F. Yang. BCI Competition 2003–Data Set IIb: Enhancing P300 Wave Detection Using ICA-Based Subspace Projections for BCI Applications. *IEEE Transactions on Biomedical Engineering*, 51(6):1067–1072, 2004.

[6] H. Serby, E. Yom-Tov, and G.F. Inbar. An improved P300-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(1):89–98, 2005.

[7] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens. An efficient p300-based brain-computer interface for disabled subjects. *Journal of Neuroscience Methods*, 167(1):115–125, 2008.

[8] P. Meinicke, M. Kaper, F. Hoppe, M. Heumann, and H. Ritter. *Advances in Neural Information Processing Systems 15,*, chapter Improving Transfer Rates in Brain Computer Interfacing: A Case Study, pages 1107–1114. MIT Press, Cambridge, MA, 2003.

[9] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw. BCI2000: A General-Purpose Brain-Computer Interface (BCI) System. *IEEE Trans. Biomedical Engineering*, 51(6):1034–1043, 2004.