An Efficient P300-based Brain-Computer Interface with Minimal Calibration Time

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1 Introduction

Brain-Computer Interfaces (BCI) are communication systems that enable subjects to send commands to computers by using only their brain activity [1]. Most existing BCI are based on ElectroEncephaloGraphy (EEG) as the measure of brain activity [1]. So far, BCI have been proven to be very promising communication and control tools for disabled people [1]. A promising brain signals used in the design of assistive BCI for disabled people is the P300, a positive waveform occuring roughly 300 ms after a rare and relevant stimulus [1, 2]. In order to use a P300-based BCI, subjects have to focus their attention on a given stimulus randomly appearing among many others, each stimulus corresponding to a given command. The appearance of the desired stimulus being rare and relevant, it is expected to trigger a P300 in the subject's brain activity. As such, detecting the P300 enables the system to identify the desired stimulus and hence the desired command. Interestingly enough, P300-based BCI have been successfully used to control a wheelchair (see, e.g., [3]) or to enable severely disabled users to spell words [2, 4].

However, current P300-based BCI as well as other BCI systems still suffer from several limitations which prevent them from being widely used [1]. One of these limitations is that to use a BCI, many examples of the subject's EEG signals must be recorded in order to calibrate the BCI, which is unconvenient and time consuming. Moreover, this calibration process generally has to be repeated at regular intervals (e.g., from one day to the other) in order to accomodate sources of variations such as changes in electrode positions or changes in the subject's mental state and fatigue level. Therefore, the calibration time should be maintained as brief as possible. Until now, reducing the calibration time of P300-based BCI has been scarcely addressed by the literature. Exceptions are the works of Li et al [5] and Lu et al [6]. Li et al suggested to use initially a BCI calibrated with few training samples, and then to incrementally adapt this BCI online, thanks to semi-supervised learning [5]. Lu et al proposed to use a subject-independent BCI, previously learnt from the data of many other subjects, also followed by online adaptation [6]. However, the main limitiation of these two approaches is that such BCI would have initially poor detection performances, becoming efficient only after adaptation. An ideal P300-based BCI would have initially high performances, even if trained with very few examples. In this paper, we propose a new P300-based BCI design which can be trained using much fewer examples than current BCI designs, without sacrifying the detection performances.

2 Method

2.1 Preprocessing of EEG signals

In order to classify the EEG signals as P300 or non-P300, we use the EEG epochs from 150 ms to 500 ms after each stimulus, as this epoch should contain the P300, if any. EEG signals from each channels are then low-pass filtered with cut-off frequency at 25 Hz, the P300 being a slow wave [1]. Finally, EEG signals are downsampled to 50 Hz in order to reduce the dimensionality of the data.

This kind of preprocessing is the one generally used in current P300-based BCI designs [7, 6, 8, 4]. With these designs, the samples from all EEG channels are concatenated into a single feature vector which is then fed into a classifier. In this paper, we term these features the "standard features". However, with our approach, the standard features are not the one fed to the classifier. Rather, we propose to perform a further feature extraction step based on Canonical Correlation Analysis (CCA).

2.2 Feature Extraction with regularized Canonical Correlation Analysis

CCA is a machine learning method used to find two directions w_X and w_Y which maximize the correlation between two random variables X and Y, once projected onto these directions [9]. It can be cast as the following optimization problem:

$$\max_{w_X, w_Y} \frac{w_X^T X^T Y w_Y}{\|X w_X\| \|Y w_Y\|} \tag{1}$$

where X and Y are represented as data matrices, with examples as rows and features as columns. This problem can be solved as a generalized eigenvalue problem [9]. If the first directions w_X and w_Y do not capture all the relationship between the two variables, multiple directions can be identified. One advantage of CCA over the classical correlation is its ability to find linear relationships between multivariate variables whereas the classical correlation can only identify linear relationships between univariate variables.

In this paper we propose to use CCA as a linear feature extraction method for P300-based BCI. More precisely, we use CCA to find directions w_F and w_L which maximize the correlation between the "standard features" F, i.e., the EEG samples, and the class labels L (P300 or non-P300). In other words we use CCA to find linear combinations of the EEG samples which best explain the class labels. Thus, the new features are the standard features F projected onto a number of directions w_F identified by CCA. Moreover, by considering only a few directions, CCA gives a new subset of features with a reduced dimensionality, making it more suitable for learning with few examples.

It should be noted that solving equation 1 requires the estimation of the sample covariance matrix of the data. Unfortunately, learning with few examples may cause this sample covariance matrix to be poorly estimated. To overcome this issue, we propose to improve the robustness of CCA by using a regularized estimator for the covariance matrix. More precisely, we used the estimator of Ledoit and Wolf [10] in order to regularized this covariance matrix in a fully automatic way. We denote the resulting CCA as Regularized CCA (RCCA).

2.3 Classification using regularized Linear Discriminant Analysis

We used a Linear Discriminant Analysis (LDA) as our classifier. LDA uses a linear hyperplane to separate data from two classes, assuming that data are normally distributed [11]. Despite its simplicity, this classifier is widely used for BCI designs as it has been shown to be one of the most efficient [11], especially for the design of P300-based BCI [7].

LDA also requires the estimation of the sample covariance matrix of the data, which may be an issue when learning from few examples. Therefore, we also regularized the LDA by using Ledoit and Wolf's estimator of the covariance matrix [10] instead of the classical sample estimator. We denote the resulting LDA as Regularized LDA (RLDA).

3 Evaluation

3.1 EEG Data acquisition

EEG signals were recorded from 10 healthy subjects who participated in 2 sessions of the P300 speller, as described in [8, 6]. With this speller, subjects can spell characters by focusing their attention on a given character displayed on a computer screen, within a 6×6 matrix of characters. The rows and columns of this matrix are successively and randomly flashing. When the row or column flashing is the one that contains the desired character, this triggers a P300 in the subject's brain activity. Indeed, this flash is a rare stimulus, relevant to the subject. The detection of this P300 enables the system to identify which row and which column contain the desired character, and as such, what is this desired character. In each session, subjects had to spell 41 given characters. For each character, ten rounds of flashing were performed, each round corresponding to the flashing of each row and each column once. The first session was used as the training set, whereas the second one was used as the test set. For each subject, both sets were composed of 4920 examples (41 characters $\times$ (6 rows + 6 columns) $\times$ 10 rounds of flashing), 820 of which corresponding to a P300 signal, i.e., the row or column flashing contained the desired character.

EEG signals were recorded using 64 EEG channels, sampled at 250 Hz. For the purpose of this study, we only considered channels Fz, Cz, Pz, PO7, PO8, OZ, P3 and P4 as they were identified as the ones giving the best classification accuracy for the P300 speller [7].

3.2 Results

In this study, we did not directly evaluate the classification accuracy of our BCI for the P300 speller. Indeed, in the classical P300 speller, EEG epochs are averaged over the different rounds of flashing, which makes the classification task easier but the application slower [8]. Here, we evaluated the performance of our BCI for the more challenging task of detecting the P300 in ”single-trial”, i.e., without averaging. In other words, we used our BCI to decide whether each EEG epoch following a flash contains a P300. This problem being a detection problem, we classically used the Area Under the ROC (Receiver Operating Characteristic) Curve (AUROCC) as the performance measure.

As an evaluation of our BCI design, we computed the AUROCC obtained on the full test set when using various number of training characters to calibrate the BCI. It should be reminded that a character corresponds to 120 examples, 20 of which belongs to the P300 class. We compared the performances obtained by our design with that of the classical P300-based BCI design, i.e., the design using the standard features as input to an LDA classifier. We also compared it with a BCI design using Principal Component Analysis (PCA) for feature extraction, a technique also popular for the design of P300-based BCI (see, e.g., [8]). For both CCA-based and PCA-based feature extraction, we extracted 50 features from the initial 136 EEG samples of each epoch (8 channels $\times$ 17 samples per channels). To assess the contribution of the different components of our BCI, we also performed these evaluations without using CCA, and/or without using regularization for CCA and/or LDA. The results obtained are displayed on Figure 1.

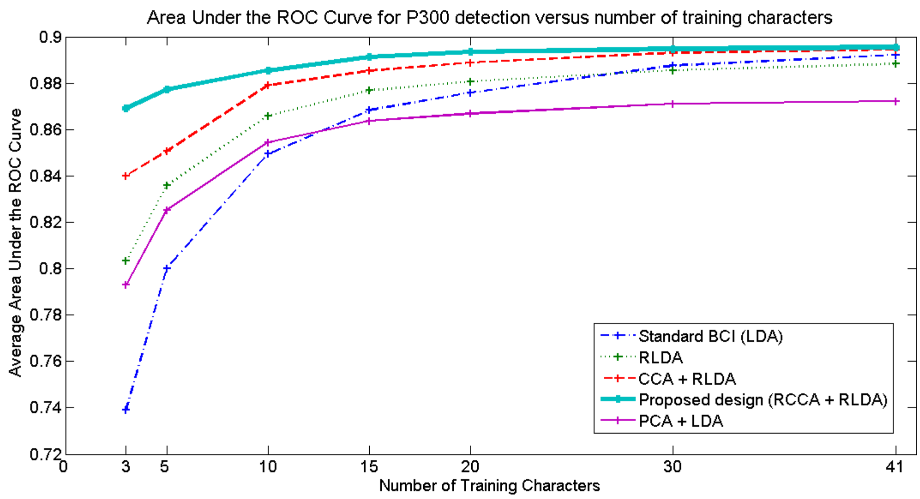

Figure 1: Average AUROCC (over the 10 subjects) versus number of characters used for training, for various methods. For reasons of readability, only values in $[0.72, 0.9]$ are displayed on the y-axis.

4 Discussion and conclusion

Results suggest that the BCI design we proposed is more efficient than both the standard and the PCA-based BCI design, especially when the number of training characters used is small. Interestingly enough, a paired t-test revealed that the average AUROCC (over all subjects and all number of training characters) obtained by our method was significantly higher than that obtained by the standard design and the PCA-based design ($p << 0.001$).

When using only 3 characters for training, our design reached an average AUROCC of 0.87, i.e., an AUROCC only 0.02 lower than that obtained by the standard design when using all 41 training characters. To reach an AUROCC of 0.87, the standard P300-based BCI design needs 5 times as many training characters as with our design, whereas the PCA-based design needs to use all 41 training characters. This suggests that our design can indeed significantly reduce the calibration time as it needs only a few training characters to reach high performances. For instance, collecting 41 training characters requires approximately 20 minutes. With our design, we just need to collect about 3 or 5 training characters to reach the same level of performance, meaning a time for data collection of roughly 2 minutes. As RCCA and RLDA are linear, fast and fully automatic methods, the whole BCI calibration remains computationally very efficient. Results also suggest that each component of our BCI (i.e., CCA, regularization of CCA and regularization of LDA) contributes to the overall performance improvement when learning from few examples. Indeed, the RCCA+RLDA design outperforms the CCA+RLDA design which in turn outperforms the "standard feature"+RLDA design, itself outperforming the "standard feature"+LDA design.

To conclude, in this paper we have proposed a new design for the P300-based BCI, in order to reduce the calibration time of the system. Our BCI is based on Regularized Canonical Correlation Analysis for feature extraction and Regularized Linear Discriminant Analysis for classification. Evaluations have suggested that this design can reach good P300 detection performances while using much less training examples than current approaches, hence effectively reducing the calibration time. Future work will explore the use of this approach in actual applications for disabled users as well as non-linear feature extraction based on kernel CCA [9].

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References

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

[2] J. Elshout and G. Garcia Molina. Review of brain-computer interfaces based on the P300 evoked potential. Technical Report PR-TN 2009/00066, Koninklijke Philips Electronics, 2009.

[3] B. Rebsamen et al. Controlling a wheelchair indoors using thought. *IEEE Intel. Sys.*, 22(2):18–24, 2007.

[4] F. Nijboer et al. A P300-based brain-computer interface for people with amyotrophic lateral sclerosis. *Clin. Neurophys.*, 119(8):1909–1916, 2008.

[5] Y. Li, C. Guan, H. Li, and Z. Chin. A self-training semi-supervised svm algorithm and its application in an eeg-based brain computer interface speller system. *Pattern Recog. Lett.*, 29(9):1285–1294, 2008.

[6] S. Lu, C. Guan, and H. Zhang. Unsupervised brain computer interface based on inter-subject information and online adaptation. *IEEE Trans. on Neural Syst. and Rehab.*, 17(2):135–145, 2009.

[7] D.J. Krusienski et al. A comparison of classification techniques for the P300 speller. *J. of Neural Eng.*, 3:299–305, 2006.

[8] M. Thulasidas, C. Guan, and J. Wu. Robust classification of EEG signal for brain-computer interface. *IEEE Trans. on Neural Syst. and Rehab.*, 14(1):24–29, 2006.

[9] D.R. Hardoon, S. Szedmak, and J. Shawe-Taylor. Canonical correlation analysis: An overview with application to learning methods. *Neural Computation*, 16(12):2639–2664, 2004.

[10] O. Ledoit and M. Wolf. A well-conditioned estimator for large-dimensional covariance matrices. *Journal of Multivariate Analysis*, 88(2):365–411, 2004.

[11] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi. A review of classification algorithms for EEG-based brain-computer interfaces. *J. of Neural Eng.*, 4:R1–R13, 2007.