Improving single-trial detection of event-related potentials through artificial deformed signals

H. Cecotti[1], B. Rivet[2]

***Abstract*— To propose a reliable and robust Brain-Computer Interface (BCI), efficient machine learning and signal processing methods have to be used. However, it is often necessary to have a sufficient number of labeled brain responses to create a model. A large database that would represent all of the possible variabilities of the signal is not always possible to obtain, because calibration sessions have to be short. In the case of BCIs based on the detection of event-related potentials (ERPs), we propose to tackle this problem by including additional deformed patterns in the training database to increase the number of labeled brain responses. The creation of the additional deformed patterns is based on two approaches: *(i)* smooth deformation fields, and *(ii)* right and left shifted signals. The evaluation is performed with data from 10 healthy subjects participating in a P300 speller experiment. The results show that small shifts of the signal allow a better estimation of both spatial filters, and a linear classifier. The best performance, AUC=0.828 ± 0.061, is obtained by combining the smooth deformation fields and the shifts, after spatial filtering, compared to AUC=0.543 ± 0.025, without additional deformed patterns. The results support the conclusion that adding signals with small deformations can significantly improve the performance of single-trial detection when the amount of training data is limited.**

I. INTRODUCTION

Brain-Computer Interfaces require improvements in different areas to be more suitable for both healthy and disabled people. Since the early work of the P300 speller [1], different improvements have been proposed for optimizing the classification of event-related potentials (ERPs) responses [2], [3], the number of repetitions of the visual stimuli [4], [5], the graphical user interface, the number of sensors [6], and the reduction of the calibration session [7]. The later point is the focus of this study. For reducing the duration of the calibration, a typical step is to optimize the duration of a session, *e.g.*, to reach a plateau in the steep learning curve of the model. For a P300 speller, the goal is to find the best trade-off between the number of characters to spell during the calibration session, and the obtained performance during the test. At the start of a session, for a calibration session, an efficient representation of the model that is able to classify different brain responses has to be created. While this model can be tuned and improved over time, thanks to the analysis of the outputs from the application and/or the monitoring of the current neural activity [8], it is an advantage to start with a model that is able to give a good performance.

The goal of single-trial detection of ERPs is to estimate a function that aims at minimizing the variability of signals from the same type of ERPs, and to maximize the difference between two signals of different types of ERPs. To create this model, we can distinguish two approaches. First, the method is adaptive: it follows the evolution of the non-stationary neural activity over time and estimates its changes. Second, the method is invariant to the deformations. It can be achieved with features that are invariant to the intra-class variabilities of the signal, *e.g.*, after spatial filtering [9]–[11], or by creating a classifier that is able to absorb all the possible intra-class variabilities with the appropriate training database.

For the improvement of BCI based on the detection of ERPs, it is critical to reduce the calibration time for estimating efficient detection models. However, reducing the calibration time implies the reduction of the available training data for tuning a classifier. By reducing the size of the training data, it is more likely to have an impact on the model estimation. To avoid such a pitfall, we propose to add deformed patterns to increase the size of the database, and to create a model invariant to small deformations. This technique requires a prior knowledge of the problem. The approach has been successfully used in other problems such as handwritten character recognition, where it was observed that small deformations (rotations, shift, small distortion) would not affect the label of the pattern [12]. The addition of deformed patterns can have two purposes: first, to increase the size of the database to improve the performance of the model; second to increase the possible variability that can be modeled by the classifier. Whereas it is relatively easy to estimate deformations that do not change the class of images that contain shapes easy to discriminate, it is more difficult to estimate alternative deformations for ERPs. However, studies in cognitive neuroscience, and particularly about the P300 ERP component indicate relationships between ERP characteristics (amplitude and latency), and behavioral traits [13]. For instance, the latency of P300 corresponds to stimulus evaluation time, and is often associated to the reaction time [14]. Its peak latency is assumed to be proportional to stimulus evaluation timing, and is sensitive to task processing demands. In addition, it can vary with individual differences in cognitive capability [15]. The remainder of this paper is as follows. First, the artificial deformations of the signal are proposed in Section II. Then, the methods and the experimental protocol are details in Section III. Finally, the results are analyzed and discussed in Section IV and V.

[1] School of Computing and Intelligent Systems, University of Ulster, Derry, Northern Ireland, UK. h.cecotti@ulster.ac.uk
[2] Gipsa lab UMR 5216 CNRS, Grenoble Universities, Saint Martin d'Heres, France.

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

II. Transformations

We consider a trial, $X \in \mathbb{R}^{N_1 \times N_s}$, for the response corresponding to the presentation of a visual stimulus (target or non-target), where N_1 is the number of sampling points, and N_s is the number of electrodes. We denote by $s_{i,j}$, the standard deviation of the feature $X(i,j)$ across all of the trials of its corresponding class (target or non-target). We propose two deformations for the creation of additional patterns in the training database. In the first deformation, F_1, we create random deformation vectors V of size $N_1 \times 1$, with values between -1 and 1. The vector of deformation is filtered with a Gaussian filter (n=3, σ=4). Then, the vector of deformation is amplified by $s_{i,j}$ on each feature, and the resulting vector is added to X. The resulting EEG trial is as follows:

$$Y_{i,j} \quad = \quad X_{i,j} + s_{i,j} \cdot V_i \tag{1}$$

The second deformation, F_2, is simply a shift of one sampling point of all the trials from the training database. The resulting EEG trial is:

$$Y_{i,j} \quad = \quad X_{i+1,j} \quad \text{(right shift in time)} \tag{2}$$

$$Y_{i,j} \quad = \quad X_{i-1,j} \quad \text{(left shift in time)} \tag{3}$$

We denote by D_{null} the database that contains only the recorded trials. D_1 and D_2 represent the training database containing both the data from D_{null}, and the additional deformed patterns from F_1 and F_2, respectively.

III. Methods

A. Experimental protocol

Ten healthy subjects (age=25.5 ± 4.4 years old, three females) participated to a P300 speller experiment. Each subject had to spell a total of 40 characters. Each subject observed the same sequence of characters. The matrix of the P300 speller is 6×6 and displayed on a 27 inches LCD screen with a brightness of 375 cd/m2. Subjects were sitting on a chair at about 60 cm from the screen, in a non shielded room. The stimulus onset asynchrony (SOA) was set to 133 ms, and the inter-stimulus interval was 66 ms. The sequence of stimuli on the rows and columns of the speller were repeated 10 times.

B. Signal acquisition

Electrodes were placed according to a subsampled version of the 10-10 system. The EEG signal was recorded on O_1, O_2, P_3, P_4, P_7, P_8, P_Z and FC_Z. F_7 and F_8 were dedicated to the ground and the reference, respectively. The amplifier is a FirstAmp (Brain Products GmbH) with a sampling frequency of 2kHz. To match real application, all of the trials were considered, and no specific artifact rejection technique was applied.

C. Signal processing

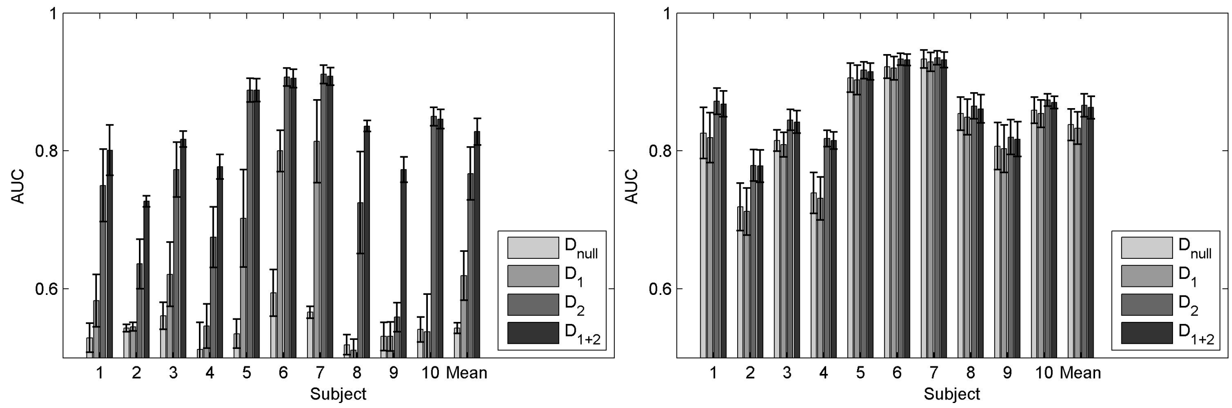
The experimental protocol suggests the presence of ERP components such as the P300 and N200 in the brain response corresponding to the presentation of a stimulus on a target. Thus, the signal could be analyzed between the beginning of the visual stimulus and less than one second after its beginning. The signal is first bandpassed filtered (Butterworth filter of order 4) with cutoff frequencies at 1 and 10.66 Hz. Then, the signal is downsampled to obtain a signal at a sampling rate equivalent to 25 Hz. For the following steps, we used the observed signal over 640 ms after the start of a visual stimulus, which corresponds to 16 sampling points ($N_1 = 16$). A shift of one point represents a shift of 40 ms in the signal.

The next step consisted of enhancing the relevant signal using the xDAWN spatial filtering approach [6], [16], [17]. In this method, spatial filters are obtained through the Rayleigh quotient by maximizing the signal-to-signal plus noise ratio (SSNR). The result of this process provides N_f spatial filters, that are ranked in terms of their SSNR. For the classification, the first four spatial filters were used. The Bayesian linear discriminant analysis (BLDA) [18], [19] classifier is considered for the detection, with the first four spatial filters as input, resulting to 64 features as the inputs of the classifier.

For the evaluation, we consider a five-fold cross validation procedure with two conditions. In the first condition (C_1), one block is used for training, and the remaining four blocks are used for the test. In the second condition (C_2), it is the opposite, four blocks are used for training, and one block is used for the test. Each block contains 160 patterns corresponding to the presentation of a target, and 640 patterns for the presentation of non-target (a block is equivalent to the trials obtained for spelling eight characters). Classifier performance is evaluated by using the area under the receiver-operator characteristic (ROC) curve (AUC). The results are presented for condition C_1 and C_2, with and without spatial filtering obtained with xDAWN.

IV. Results

The performance for single-trial detection, without considering the technique D_2 to estimate the spatial filters, is depicted for both conditions C_1 and C_2 in Fig. 1. The largest difference of performance across the databases with deformed patterns is observed in C_1, as this condition has few training trials for estimating the parameters of the classifier. Without the addition of deformed patterns, for C_1, the mean AUC is 0.543 ± 0.025. With D_1, D_2, and D_{1+2}, the AUC is 0.619 ± 0.113, 0.767 ± 0.121, and 0.828 ± 0.061, respectively. With only eight spelt characters, the typical approach does not allow to create a model to correctly classify trials corresponding to targets, versus trials corresponding to non-targets, as the performance is only 0.543, just above chance level. However, with the addition of D_{1+2}, the AUC of 0.828 shows that it is possible to obtain a reliable performance. A repeated measures analysis of variance (ANOVA) confirmed a difference across the training conditions ($F(3, 27) = 51.29$,



(a) C_1 (b) C_2

Fig. 1. AUC for each subject and each condition, **without D_2 for estimating spatial filters**. The error bars indicate the standard errors.

p<10e-9). Pairwise t-test comparisons with a Bonferroni correction indicate that the main source of difference is due to D_2 that allows the main improvement. For C_2, the mean AUC is 0.838 ± 0.072. With D_1, D_2, and D_{1+2}, the AUC is 0.833 ± 0.074, 0.866 ± 0.052, and 0.863 ± 0.052, respectively. With D_{1+2}, the mean AUC only increases from 0.838 to 0.863. The repeated ANOVA also confirmed a difference across the training conditions ($F(3, 27) = 12.16$, p<10e-5). In addition, those results show that the performance is slightly equivalent between a calibration session with eight characters and deformed patterns, and a calibration session with 32 characters.

As the trials shifted in time provide an increase of performance, we also evaluate the performance when spatial filtering is used and when F_2 is applied on the training database before estimating the spatial filters. When the D_2 is used for the estimation of the spatial filters, the results are equivalent to when it is not used and follow the same pattern of performance. The results are depicted in Fig. 2. Particularly, the performance for the condition C_1 is 0.539 ± 0.027 for D_{null}, 0.623 ± 0.113 for D_1, 0.765 ± 0.125 for D_2, and 0.827 ± 0.061 for D_{1+2} ($F(3, 27) = 49.06$, p<10e-10). For C_2, the performance is 0.839 ± 0.072, 0.833 ± 0.074, 0.866 ± 0.052, and 0.863 ± 0.052 for D_{null}, D_1, D_2, and D_{1+2}, respectively ($F(3, 27) = 11.99$, p<10e-4). The results show that D_2, which has the main effect on the classifier, does not provide any improvement for the spatial filters estimated with the xDAWN framework.

Finally, the performance that is obtained without spatial filtering is depicted in Fig. 3. The pattern of performance is similar to the previous experimental conditions, *i.e.*, there is an increase of performance with the addition of the shifted patterns. With C_1, the AUC is 0.689 ± 0.084, 0.687 ± 0.084, 0.761 ± 0.051, and 0.762 ± 0.050 for D_{null}, D_1, D_2, and D_{1+2}, respectively ($F(3, 27) = 16.75$, p<10e-5). By considering a larger training database with C_2, the AUC is 0.766 ± 0.060, 0.765 ± 0.061, 0.796 ± 0.046, and 0.796 ± 0.046 ($F(3, 27) = 12.23$, p<10e-4). Without spatial filtering, and with a large training database, the increase of performance with D_2 is not as important as when spatial filtering is used.

V. Conclusion and Discussion

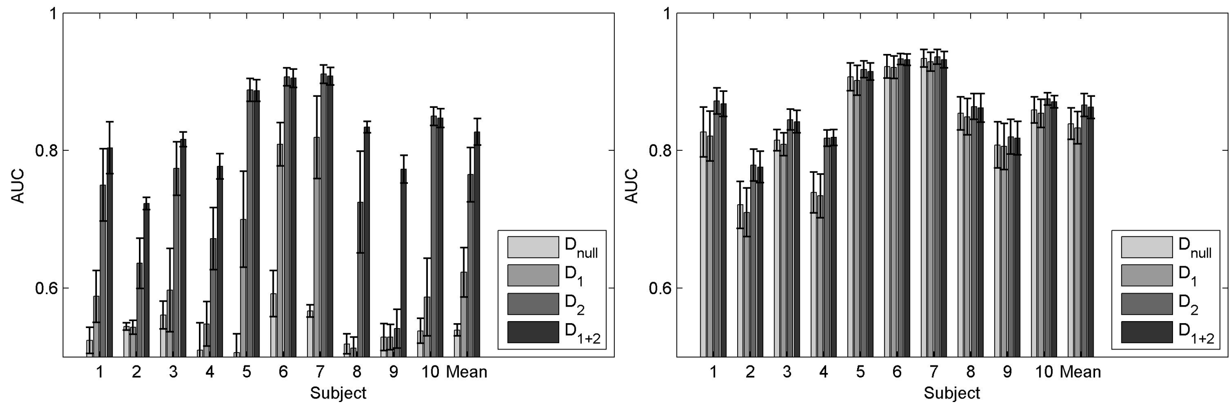
In this study, we have shown how a training database can be extended through artificial deformations of the EEG signal after spatial filtering. Thanks to the addition of new patterns in a database, single-trial detection performance can be significantly improved when the number of available trials in the database is limited. We have shown that with only a training session that contains 8 characters (≈128 seconds), it was possible to achieve performance almost equivalent to training session that are four times longer. The proposed approach can be an alternative to solutions that search invariant features. By trying to provide to the classifier a maximum number of representative trials, it is possible to increase the performance of the classifier. With the chosen sampling rate of 25 Hz, we have shown that adding shifted trials of one sampling point, which corresponds to 40 ms, it was possible to increase the performance of the classifier. While it could be assumed that a jitter in the stimulus onsets can be an obstacle for the estimation of a model for single-trial detection, we have shown that the addition of shifted patterns was beneficial when the calibration session is short. By comparing two conditions with a different number of patterns for the training and the test, we have shown that the performance can completely change and lead to a different conclusion on the expected performance for a BCI user. Furthermore, the parameters for the creation of the smooth deformed fields D_1 were not optimized, other parameters may provide better results. Further investigations on the spatial projection of the ERPs, and the variability of their amplitudes and latencies, could provide key insight on how artificial ERPs could be generated.

Acknowledgment

This work was partially funded by Grenoble-INP SEI CAICO project and ERC AdG-2012-320864-CHESS.

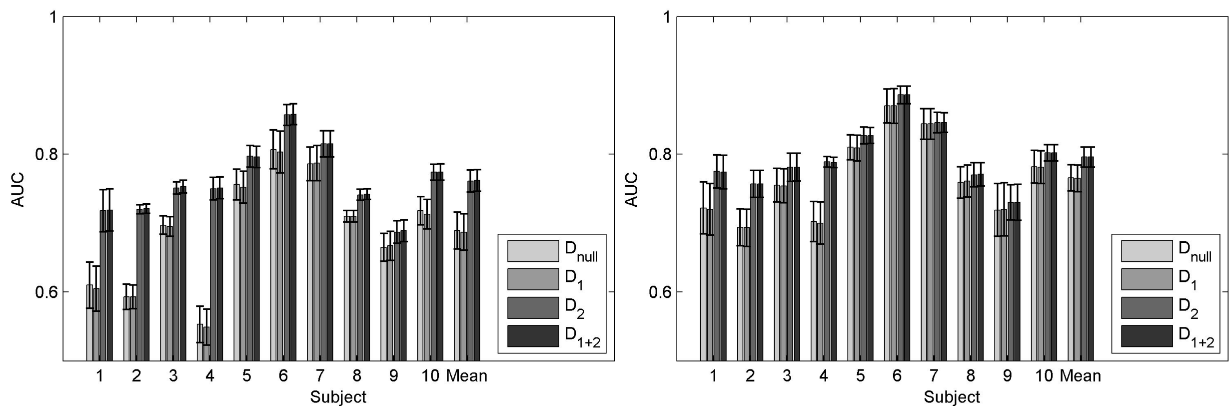
References

[1] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr. Clin. Neurophysiol.*, vol. 70, pp. 510–523, 1988.



(a) C_1 (b) C_2

Fig. 2. AUC for each subject and each condition, **with D_2 for estimating spatial filters**. The error bars indicate the standard errors.



(a) C_1 (b) C_2

Fig. 3. AUC for each subject and each condition, **with no spatial filters**. The error bars indicate the standard errors.

[2] H. Cecotti and A. Gräser, "Convolutional neural networks for P300 detection with application to brain-computer interfaces," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 33, no. 3, pp. 433–445, 2011.

[3] A. Rakotomamonjy and V. Guigue, "BCI competition iii : Dataset ii - ensemble of SVMs for BCI P300 speller," *IEEE Trans. Biomedical Engineering*, vol. 55, no. 3, pp. 1147–1154, 2008.

[4] M. Shreuder, J. Höne, B. Blankertz, S. Haufe, T. Dickhaus, and M. Tangermann, "Optimizing event-related potential based brain-computer interface: a systematic evaluation of dynamic stopping methods," *J. Neural Eng.*, vol. 10, p. 036025, 2013.

[5] H. Zhang, C. Guan, and C. Wang, "Asynchronous P300-based brain-computer interface: a computational approach with statistical models," *IEEE trans. Biomed. Eng.*, vol. 55, no. 6, pp. 1754–63, 2008.

[6] H. Cecotti, B. Rivet, M. Congedo, C. Jutten, O. Bertrand, E. Maby, and J. Mattout, "A robust sensor selection method for P300 brain-computer interfaces," *J. Neural Eng.*, vol. 8, p. 016001, 2011.

[7] B. Rivet, H. Cecotti, M. Perrin, E. Maby, and J. Mattout, "Adaptive training session for a P300 speller brain-computer interface," *Journal of Physiology (Paris)*, vol. 105, no. 1-3, pp. 123–129, 2011.

[8] Q. Zhao, L. Zhang, A. Cichocki, and J. Li, "Incremental common spatial pattern algorithm for BCI," *Neural Networks - IJCNN*, pp. 2656–2659, 2008.

[9] B. Blankertz, M. Kawanabe, R. Tomioka, F. Hohlefeld, V. Nikulin, and K.-R. Müller, "Invariant common spatial patterns: Alleviating nonstationarities in brain-computer interfacing," *Advances in Neural Information Processing Systems*, vol. 20, pp. 1–8, 2008.

[10] W. Samek, C. Vidaurre, K. R. Müller, and M. Kawanabe, "Stationary common spatial patterns for braincomputer interfacing," *J. Neural Eng.*, vol. 9, p. 026013, 2012.

[11] H. Cecotti, M. Eckstein, and B. Giesbrecht, "Single-trial classification of event-related potentials in rapid serial visual presentation tasks using supervised spatial filtering," *IEEE Trans. Neural Networks and Learning Systems*, pp. 1–13, 2014.

[12] P. Y. Simard, D. Steinkraus, and J. C. Platt, "Best practices for convolutional neural networks applied to visual document analysis," *7th International Conference on Document Analysis and Recognition*, pp. 958–962, 2003.

[13] J. Polich and A. Kokb, "Cognitive and biological determinants of P300: an integrative review," *Biological Psychology*, vol. 41, pp. 103–146, 1995.

[14] M. Kutas, G. McCarthy, and E. Donchin, "Augmenting mental chronometry: the p300 as a measure of stimulus evaluation time," *Science*, vol. 197, no. 4305, pp. 792–5, 1977.

[15] J. Polich, "Updating P300: An integrative theory of P3a and P3b," *Clinical Neurophysiology*, vol. 118, pp. 2128–2148, 2007.

[16] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, "xDAWN algorithm to enhance evoked potentials: application to brain-computer interface," *IEEE Trans Biomed Eng.*, vol. 56, no. 8, pp. 2035–43, 2009.

[17] B. Rivet and A. Souloumiac, "Optimal linear spatial filters for event-related potentials based on a spatio-temporal model: Asymptotical performance analysis," *Signal Processing*, vol. 93, no. 2, pp. 387–398, 2013.

[18] D. J. C. MacKay, "Bayesian interpolation," *Neural Comput.*, vol. 4, no. 3, pp. 415–447, 1992.

[19] U. Hoffmann, J. Vesin, K. Diserens, and T. Ebrahimi, "An efficient P300-based brain-computer interface for disabled subjects," *Journal of Neuroscience Methods*, vol. 167, no. 1, pp. 115–125, 2008.