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

H. Cecotti<sup>1</sup>, B. Rivet<sup>2</sup>

**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,  $AUC=0.828 \pm 0.061$ , is obtained by combining the smooth deformation fields and the shifts, after spatial filtering, compared to  $AUC=0.543 \pm 0.025$ , 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], [10], 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 [11]. 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 [12]. For instance, the latency of P300 corresponds to stimulus evaluation time [13]. The latency of the P300 is often associated to the reaction time. 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 [14]. 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.

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## 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 fields of size  $N_1 \times 1$ , with values between -1 and 1. The vector of deformation is filtered with a Gaussian filter ( $n=3$ ,  $\sigma=4$ ). Then, the vector of deformation is amplified by  $s_{i,j}$  on each feature, and the resulting vector is added to  $X$ . The second deformation,  $F_2$ , is simply a shift of one sampling point of all the trials from the training database (shifts are applied left and right). In the experiments, we compare the performance obtained with different training databases. 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 =  $25.5 \pm 4.4$  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  $6 \times 6$  and displayed on a 27 inches LCD screen with a brightness of 375cd/m<sup>2</sup>. Subjects were sitting on a chair at about 60cm from the screen, in a non shielded room. The stimulus onset asynchrony (SOA) was set to 133ms, and the inter-stimulus interval was 66ms. 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  $FC_Z$ .  $F7$  and  $F8$  were dedicated to the ground and the reference, respectively (Fig 1). 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 a P300 in the brain response corresponding to the presentation of 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 10.66Hz. Then, the signal is downsampled to obtain a signal at a sampling rate equivalent to 25Hz. For the following steps, we used the observed signal over 640ms

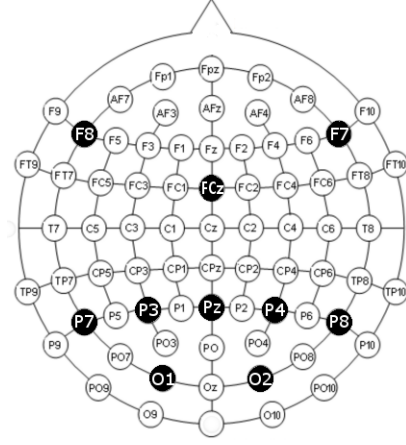


Fig. 1. Electrode placement in the international 10-10 system [15].

after the start of a visual stimulus, which corresponds to 16 sampling points ( $N_e = 16$ ).

The next step consisted of enhancing the relevant signal using the xDAWN spatial filtering approach [16], [17], [6]. 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).

## IV. RESULTS

The results are presented for condition  $C_1$  and  $C_2$ , with and without spatial filtering. When spatial filtering is used, the AUC is also given for when  $F_2$  is applied on the training database before estimating the spatial filters.

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. 2. 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  $0.543 \pm 0.025$ . With  $D_1$ ,  $D_2$ , and  $D_{1+2}$ , the AUC is  $0.619 \pm 0.113$ ,  $0.767 \pm 0.121$ , and  $0.828 \pm 0.061$ , respectively. With only eight spelt characters, the typical approach does

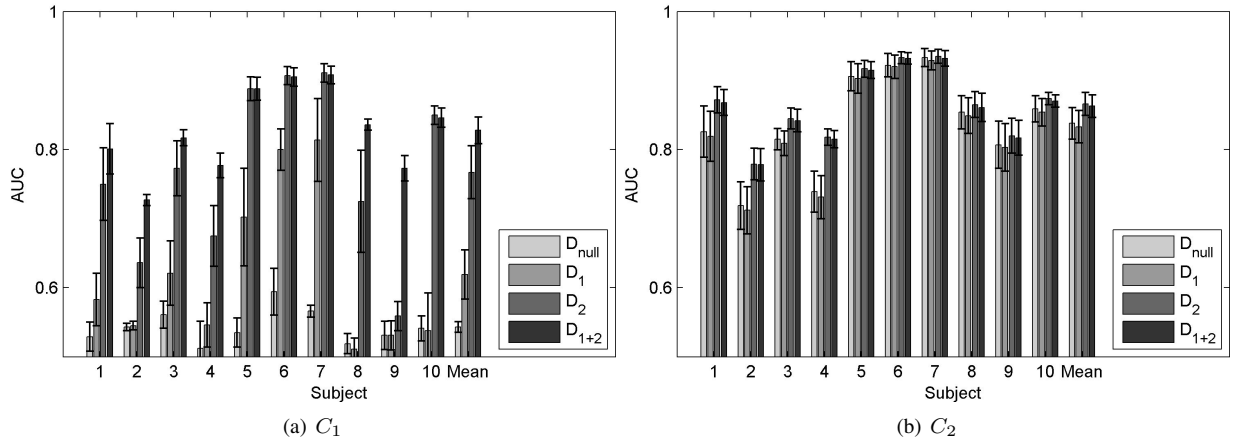


Fig. 2. AUC for each subject and each condition, **without  $D_2$  for estimating spatial filters**. The error bars indicate the standard errors.

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 ( $F(3, 9) = 51.29$ ,  $p < 10e-9$ ). Pairwise t-test comparisons indicate that the main source of difference is due to  $D_2$  that allows the main improvement. For  $C_2$ , the mean AUC is  $0.838 \pm 0.072$ . With  $D_1$ ,  $D_2$ , and  $D_{1+2}$ , the AUC is  $0.833 \pm 0.074$ ,  $0.866 \pm 0.052$ , and  $0.863 \pm 0.052$ , 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 ( $F(3, 9) = 12.16$ ,  $p < 10e-5$ ). 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.

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. 3. Particularly, the performance for the condition  $C_1$  is  $0.539 \pm 0.027$  for  $D_{null}$ ,  $0.623 \pm 0.113$  for  $D_1$ ,  $0.765 \pm 0.125$  for  $D_2$ , and  $0.827 \pm 0.061$  for  $D_{1+2}$ . For  $C_2$ , the performance is  $0.839 \pm 0.072$ ,  $0.833 \pm 0.074$ ,  $0.866 \pm 0.052$ , and  $0.863 \pm 0.052$  for  $D_{null}$ ,  $D_1$ ,  $D_2$ , and  $D_{1+2}$ , respectively. 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. 4. 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  $0.689 \pm 0.084$ ,  $0.687 \pm 0.084$ ,  $0.761 \pm 0.051$ , and  $0.762 \pm 0.050$  for  $D_{null}$ ,  $D_1$ ,  $D_2$ , and  $D_{1+2}$ , respectively. By considering a larger training database with  $C_2$ , the AUC is  $0.766 \pm 0.060$ ,  $0.765 \pm 0.061$ ,  $0.796 \pm 0.046$ , and  $0.796 \pm 0.046$ . 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, 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 25Hz, we have shown that adding shifted trials of one sampling point, which corresponds to 40ms, 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. 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.

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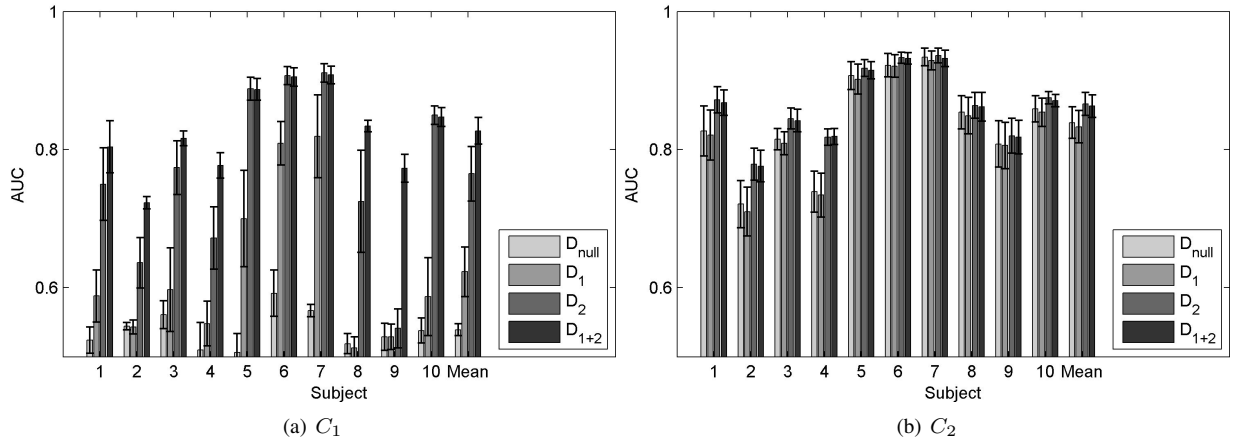


Fig. 3. AUC for each subject and each condition, with  $D_2$  for estimating spatial filters. The error bars indicate the standard errors.

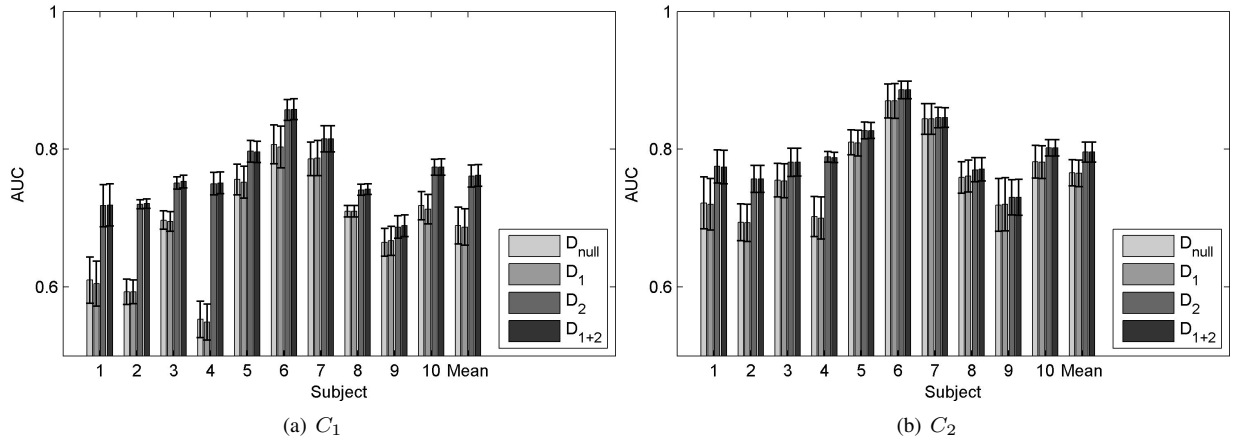


Fig. 4. AUC for each subject and each condition, with no spatial filters. The error bars indicate the standard errors.

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