The Subspace Regularization Method Improves ErrP Detection by EEGNET in BCI Experiments

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Abstract: In this study, the subspace regularization method was applied on the Electroencephalographic (EEG) signal recorded during stimulation of the Error Potential (ErrP) in order to improve the detection of the latter. The ErrP is stimulated through the presentation of an erroneous event to the subject. The recorded signals were processed with the subspace regularization method to remove the background EEG not related to the erroneous event. Then, the ErrP and Non–ErrP epochs (both raw and processed with the proposed method) were classified using EEGNET, a Convolutional Neural Network considered golden standard for EEG classification. The results show that elaborating the signals with the proposed method highlight the typical characteristics of the ErrP epochs both in temporal and frequency domain. Moreover, the classification metrics evaluated, always increase if compared to not processed signal (i.e. maximum increase in accuracy, balanced accuracy and F1-score are of 7.7%, 10.1% and 11% respectively). These findings suggest that the subspace regularization method can improve the performance of ErrP-based Brain Computer Interfaces (BCI) and can be used also in real time application and for asynchronous classification of erroneous events.

1 INTRODUCTION

Brain Computer Interfaces (BCI) are technologies that allow to control an external device using subject's brain activity (Wolpaw et al., 2000). BCI are particularly used for rehabilitation in subjects that experienced the loss of motor or cognitive skills.

To have a representation of the activity present at the scalp level, the Electroencephalographic signal (EEG) is usually recorded due to its intrinsic non invasive nature and its high temporal resolution. Depending on the kind of stimulus presented to the subject, different EEG responses can be obtained and, therefore, different EEG-based BCI systems can be designed. In this paper the focus is set on the Error Potential (ErrP), an event-related potential that arises whenever an error is detected by a user, both if the error is committed by an external device or by the user itself (Falkenstein et al., 2000). The activity is located in the medio–frontal areas of the brain, in particular in the anterior cingulate cortex (Holroyd and M.Coles, 2002), and, depending on the task, different ErrPs types can be distinguished. The realization follows a stereotypical shape characterized by a negative peak occurring at 250 ms after the error, a positive peak at 320 ms and a negative peak at 450 ms (Ferrez and del R. Millan, 2008). In the frequency domain the EEG signal recorded after the erroneous event is particularly localized in the $\delta(1-3Hz)$ and $\theta(5-8Hz)$ brain rhythms (Spuler and Niethammer, 2015)(Abhang et al., 2016).

In literature, the ErrP detection in BCI application is mainly employed to correct the output of BCIs that are based on other paradigms. For example in (Seno et al., 2010), the authors developed a P300 speller, a BCI able to detect the letter chosen by the user from a grid of letters. The detection of the ErrP in this case is used for correcting the letter identified by the system if it is not the one intended by the user. Since the feedback given to the subject is crucial in any BCI experiment, the detection of an ErrP during a correct trial may lead to frustration and, thus, to less involvement of the participant during the trial (Lotte, 2012).

Moreover, the detection of erroneous events is finding application also in other fields, where the correction of an external device can drastically improve the effectiveness of the device itself (e.g. autonomous driving (Belcher et al., 2022)). These examples highlight the importance of having a correct classification

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of the ErrP and excluding false postives as much as possible. The advances in machine learning and deep learning algorithms have enhanced the detection of Evoked Potentials (EP) (Z.Cao, 2020), but still remains difficult to separate the signal of interest from the background EEG in the single sweep analysis. These difficulties is reflected in unsatisfactory performances and high values of false positives during classification.

In this study, we applied a method used in literature (i.e. subspace regularization (Karjalainen et al., 1999)) for estimating the sources of the ErrP single sweeps and we analyzed whether this elaboration of the signal may improve the classification performance in distinguishing between erroneous and correct events. Moreover, the elaborated signal has also been analyzed in order to assess if the characteristics of the ErrP are preserved, or even enhanced, by this method.

2 METHODS

2.1 Dataset

The dataset used in this project is the open access BCI dataset of *BNCI Horizon 2020: Monitoring error-related potentials* (BNCI, 2020). It consists of EEG recordings obtained during an ErrP-specific experiment performed on six subjects (mean age 27.83 ± 2.23) in two recording sessions (Chavarriaga and Millan, 2010).

The experimental paradigm consists of reaching a target (i.e. a coloured square) through a moving cursor. The working area is constituted by 20 possible horizontal positions where the cursor and the target square may be located. At each time step (2 seconds each), the cursor moves a step toward the location of the square. Once the target is reached, the cursor remains in place and a new target location appears. Subjects are asked to monitor the position of the cursor (without having any control over it), knowing that the objective is to reach the target. In order to elicit the ErrP, at each time step, the cursor is moved in the wrong direction with 20% of probability.

The recording session consists of 10 blocks of 3 minutes each, including approximately 50 cursor movements per block. Subjects performed two recording sessions with a gap of several weeks. For each session, the EEG signal is recorded (512 Hz sampling frequency) with 64 electrodes using a BioSemi ActiveTwo system. Electrodes are placed according to the 10-20 International System. More details about the experimental setup and the recorded signals are published in (Chavarriaga and Millan, 2010).

The data–set is largely unbalanced: it is constituted by 6437 epochs of which 1322 include the ErrP.

2.2 Preprocessing

The raw EEG data are spatially filtered with the Common Average Rereferencing (CAR) method and then band passed filtered between 1-40 Hz in order to remove the noise at higher frequencies. Data are then downsampled at 64Hz and divided in epochs of interval [0 1]s from stimulus onset in order to cover the expected ErrP latencies. No artifact removal (e.g. Indipendent Component Analysis) algorithm has been applied in view of a real-time application of the method. The preprocessing pipeline has been implemented in Python with the MNE library (Gramfort et al., 2013).

2.3 Subspace Regularization Method

The subspace regularization method has been presented in (Karjalainen et al., 1999) and has been used for single trial estimation of P300 EP.

The recorded signal can be described as a linear combination of the EP of interest (i.e. source) and some noise introduced with the measurements. The EEG signal z is described as:

$$z = s + v = H\theta + v \tag{1}$$

where s is the source signal and v is the backgorund EEG. In particular the source is described as a linear combination of some basis vectors (i.e. H) depending on the measurements and so, in linear algebra, s lie in the subspace described by these basis vectors.

The subspace regularization method aims to find the optimal parameters θ by searching the optimal basis vectors and minimizing the contribution given by an estimated v.

In our study we decided to use as noise the background EEG not related to the stimulation and estimated during the second before the stimulation. Thus, the estimation of s is reduced to the solution of following formula:

$$s = H(H^T * C_v^{-1} H + \alpha^2 H^T (I - K_s K_s^T) H)^{-1} H^T C_v^{-1} z \tag{2}$$

where H is a set of basis vector (Gaussian waveforms) than span along the signal, K_s is the eigenvector matrix of the correlation matrix of z, C_v is the covariance matrix of the noise v and α is defined as the regularization parameter that can be chosen experimentally.

From the preprocessed ErrP and Non–ErrP epochs, the sources are extracted with this method and used for classification purposes.

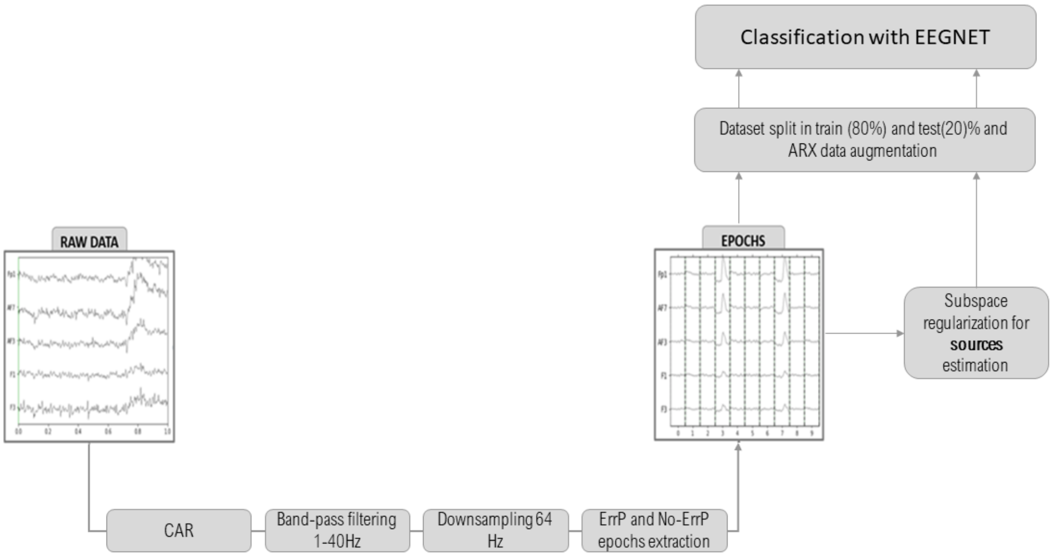

Figure 1: Pipeline of the preprocessing and classification of the ErrP and Non-ErrP EEG measurements.

2.4 ErrP Classification

In order to classify the extracted epochs, the EEGNET (Lawhern et al., 2018) Convolutional Neural Network have been employed. The authors of this CNN proved that it has good generalize ability in different BCI paradigms and that is why it has been chosen also in this paper. The architecture is composed by the peculiar Depthwise and Separable Convolutional layers in combination with the classical dropout and batch normalization layers. The last layer is a typical fully connected layer for classification output. A majority vote approach is employed to obtain the prediction label for the test set: it has been chosen since it would outperform the best classifier if the classifiers make independent errors (Orrite et al., 2008). As input of EEGNET both the subspace regularized and not processed EEG signals coming from all channels were used. It has been decided to consider all the electrodes in order to not lose any information.

The dataset of each subject was shuffled to ensure heterogeneous distribution of data an then it was divided, using 20% of the data as test set, while the remaining data were divided in training (80%) and validation set (20%). The performance in test was assessed first with the raw data and then the network was re-trained and tested with the subspace regularized epochs and differences in performances was analyzed. Stratified 5-folds cross-validation is performed on the validation set. The results will be presented in terms of test accuracy, balanced accuracy and F1-score for assessing the classifier performance.

Due to the high unbalance of the two classes, for both training processes a data augmentation algorithm has been used: in particular we decided to use the ARX-based method proposed in (Farabbi et al., 2021).

The performance of the classifier has been analysed both in two ways: subject-wise, where the classifier has been trained and tested separately for each subject in order to assess the individual performance; population-wise, where data coming from all subjects were considered as one in order to assess an overall generalize ability of the classifier.

The complete pipeline of the preprocessing and classification is reported in Fig.1.

3 RESULTS

3.1 Sources Estimation

In Fig.2.A are reported the Grand Average of the ErrP signal without (blue) and with subspace regularization (orange) at the electrode FCz (the most involved in ErrP stimulation) for one subject as an example. It is worth to notice that the source estimated with the proposed method, follows the original waveform, excluding the high frequency components and reducing the peaks given by the background EEG that is not related with the EP of interest. Moreover, the main characteristics of the ErrP are preserved with the typical negative and positive peaks.

This can be noticed also in the frequency domain (Fig.2.B): the PSD of the estimated source (blue) is mostly activated in the δ and θ bands and no component after 10Hz.

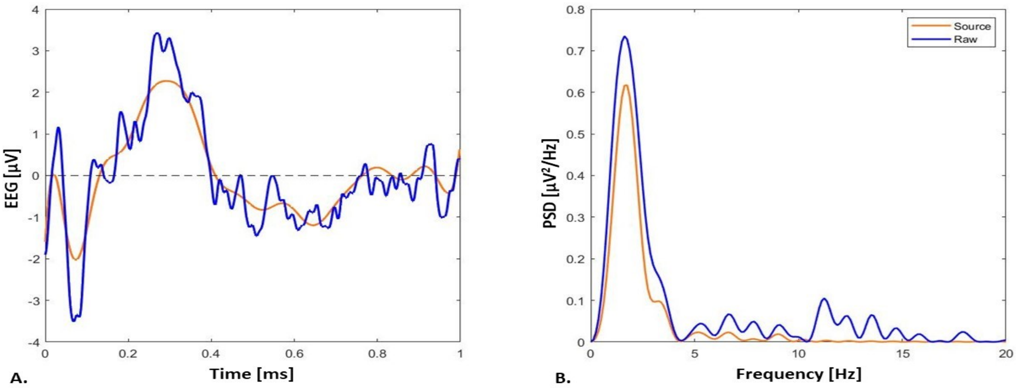

Figure 2: ErrP epoch in time domain (A) and the PSD in frequency domain (B) for electrode FCz. In blue is reported the ErrP signal processed with the subspace regularization method, while in orange the signal with no processing.

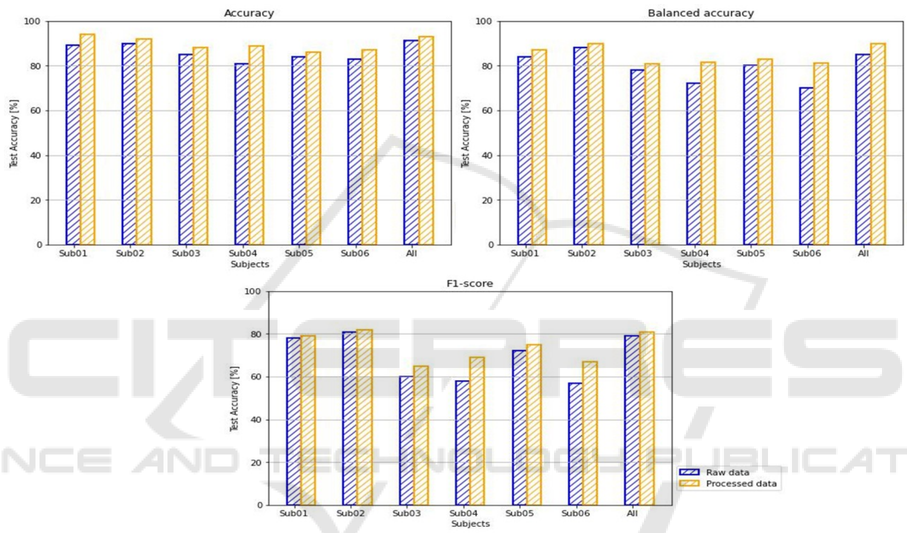

Figure 3: EEGNET performance in terms of accuracy, balanced accuracy and F1 score. The score for each subject and of the whole participants considered as one are reported. In blue the metrics with non processed signals used as input for EEGNET, while in orange the signals with subspace regularization.

3.2 EEGNET Performances

Concerning the performance of the EEGNET classifier, we reported in Fig.3 the results in terms of accuracy, balanced accuracy and F1-score using signals processed with the subspace regularization method (in orange) and the ones with no processing (in blue).

In the figure are reported the metrics obtained for each subject and the ones considering the signals coming from all participants as one.

We can observe that in all cases the metrics get higher values, with maximum increases of 10.1% for the balanced accuracy, 7.7% for the accuracy and 11% for the F1-score. Moreover, it is worth to notice that the subjects that achieved lower performances using not elaborated signals are the ones that resulted in a larger increment of the metrics.

4 DISCUSSION

The obtained results suggest that the subspace regularization method may be optimal in ErrP signal processing in order to improve the classification performances of the ErrP detector. It is interesting to observe that also subjects with low accuracy metrics (i.e. subjects #3, #4 and #6) when no processing was implemented, resulted in good performance when processed with the proposed method.

Moreover, the signals obtained after the subspace regularization enhance the main characteristics of the subject, highlighting positive and negative peaks at the expected latencies and focusing the brain rhythm in the δ band, suggesting that the activation of higher frequencies (observable in the non processed signal) are not related to the ErrP-stimulated response, but to background EEG. Thus, not only the method seems to give a good estimate of the sweep of interest, but also seems appropriate to estimate the background EEG from the second before the onset of the stimulus.

5 CONCLUSION

In this paper we presented a study on the effect of applying subspace regularization method to ErrP in terms of signal processing and of classification metrics using a Convolutional Neural Network for distinguishing between ErrP and Non–ErrP realizations.
The proposed pre-processing method enhances the main characteristics of the ErrP signal and improves the classification performance in each subject and for each evaluated metric.

Since the subspace regularization method is fast in terms of computational time, it can be adopted also in real time BCI classification based on the ErrP Evoked Potential. Moreover, the proposed method can be applied also to enhance asynchronous classification of ErrP events (or in general of Evoked Potentials).

REFERENCES

Abhang, P., Gawali, B., and Mehrotra, S. (2016). Technological basics of eeg recording and operation of apparatus. *Introduction to EEG- and Speech-Based Emotion Recognition*.

Belcher, M., I.Hwuang, S.Bhattacharya, Hairston, W., and Metcalfe, J. (2022). Eeg-based prediction of driving events from passenger cognitive state using morlet wavelet and evoked responses. *Transportation Engineering*, 8:100–107.

BNCI (2020). http://bnci-horizon-2020.eu/database/dataset.

Chavarriaga, R. and Millan, J. d. R. (2010). Learning from eeg error-related potentials in noninvasive brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(4):381–388.

Falkenstein, M., Hoormann, J., Christ, S., and J.Hohnsbein (2000). Erp components on reaction errors and their functional significance: a tutorial. *Biological psychology*, 51(2-3):87–107.

Farabbi, A., Aloia, V., and Mainardi, L. (2021). Arx-based eeg data balancing for error potential bci. *Journal of Neural ENgineering*, 19(3):1741–2552.

Ferrez, W. and del R. Millan, J. (2008). Error-related eeg potentials generated during simulated brain-computer interaction. ieee transactions on biomedical engineering. *IEEE transactions on bio-medical engineering*, 55.3:923–929.

Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., and Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(267):1–13.

Holroyd and M.Coles (2002). The neural basis of human error processing: Reinforcement learning, dopamine and the error-related negativity. *Psychological Review*, pages 679–709.

Karjalainen, P., Kaipio, J., Koistinen, A., and Vauhkonen, M. (1999). Subspace regularization method for the single-trial estimation of evoked potentials. *IEEE Transactions on Biomedical Engineering*, 46:849–860.

Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., and Lance, B. J. (2018). Eegnet: a compact convolutional neural network for eeg-based brain-computer interfaces. *Journal of Neural Engineering*, 15(5).

Lotte, F. (2012). On the need for alternative feedback training approaches for bci. *Berlin Brain-Computer Interface Workshop*.

Orrite, C., Rodríguez, M., Francisco, Martínez, and Michael Fairhurst, M. (2008). Classifier ensemble generation for the majority vote rule. *Progress in Pattern Recognition, Image Analysis and Applications*, 5197:340–347.

Seno, B. D., Matteucci, M., and Mainardi, L. (2010). Online detection of p300 and error potentials in a bci speller. *Computational intelligence and neuroscience*, 2010.

Spuler, M. and Niethammer, C. (2015). Error-related potentials during continuous feedback: using eeg to detect errors of different type and severity. *Frontiers in human neuroscience*, 9:155.

Wolpaw, J., Birbaumer, N., Heetderks, W., D.J.McFarland, Peckham, P., Schalk, G., Donchin, E., Quatrano, L., Robinson, C., and Vaughan, T. (2000). Brain-computer interface technology: a review of the first international meeting. *IEEE transactions on rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 8(2):164–173.

Z.Cao (2020). A review of artificial intelligence for eeg based brain computer interfaces and applications. *Brain Science Advances*, 6(3):162–170.