**Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006**

Single Trial P300 detection based on the Empirical Mode Decomposition

Teodoro Solis-Escalante, Gerardo Gabriel Gentiletti, Oscar Yañez-Suarez

Abstract— **We present a new method for single trial detection of P300 evoked responses. The features used to classify are the coefficients of a least-squaress fit of a single EEG epoch to the Intrinsecal Mode Functions of an Empirical Mode Decomposition of the averaged event response from a P300 training set. Support Vector Machines with a linear kernel are used to classify the epochs and receiver operating characteristic analysis is used to evaluate our method's performance.**

I. INTRODUCTION

An expanding research field on Biomedical Engineering is the design of Brain-Computer Interfaces (BCI). In recent years the scientific community has focused its efforts in providing patients suffering a motor disability with a way to communicate or interact with the external world. Many BCI system are based in the analysis of the EEG Event Related Potentials (ERP) such as the P300 oddball event response [1]. The most reliable method to detect a P300 is the averaging of several epochs that contain the ERP, however the number of epochs is large (at least five preprocessed epochs) and it could take a few minutes to process a meaningful message. A proposed solution to this problem is the ERP detection in a single epoch of EEG [2].

The most difficult part of the detection problem is the feature extraction due to the poor signal to noise ratio (SNR) of a single epoch. The P300 is a positive deflection that ocurrs around 300 ms after the stimuli; this deflection is clearly a low-frecuency signals, therefore a method to filter or decompose the signal could be used to spot this wave. The Empirical Mode Decomposition (EMD) is a method of analysis that represents a signal as the sum of a zero-mean amplitude-frecuency modulated signal set [3]. Each element of this set is known as a Intrinsical Mode Function (IMF).

Based on the IMF, different feature extraction schemes could be design. Once a number of features have been extracted for each epoch a classifier is used to perform the detection task. We have selected the Support Vector Machines (SVM) wich are classifiers that adjust an hyperplane to the training sets minimizing the distance of the decision boundary to the data [4].

This work was supported by CONACyT with a scholarship granted to Teodoro Solis-Escalante. #193305

Teodoro Solis-Escalante and Oscar Yañez-Suarez are with the Neuroimaging Laboratory, Department of Electrical Engineering, Universidad Autónoma Metropolitana - Iztapalapa, México.

Gerardo Gabriel Gentiletti is with the Universidad Nacional de Entre Rios, Argentina.

The performance and validation of the classifiers are typically reported as a set of parameters that give information about the number of patterns correctly classified. The basic parameters are Sensitivity and Specificity ; however these measurements are very sensible to the distribution of the data. A better performance measure of the performance is the area under the relative operation curve (ROC) [5]. Applications of ROC performance measurement to SVM classification has been reported in [6].

II. METHODOLOGY

A. Data Set

We used dataset II from the Third Edition of the BCI Competiton [7]. We have been working with this data in many projects, and we believe that it could be considered as an standard to provide a way to objectively compare different algorithms.

The dataset contains recordings of two subjects using the BCI2000 speller [8]; each run consists of 64 channels sampled at 240Hz with 15 runs per character. In this work we generate two subsets for each subject, one for training and one for testing. The training sets consist of 40 character recordings with equal prevalence of both classes, the test sets consist of 5 character recordings with normal prevalence for both classes (one P300 out of six trials). The characters for each subset were randomly selected. The trend and the temporal mean were subtracted from the sets and all epochs were scaled to the interval $[-1, 1]$. No further preprocessing was made (e.g. filtering). To reduce the size of the datasets, a 0 to 600 ms rectangular window was used to clip each epoch to 145 samples. Only electrodes FC_1, FC_Z, FC_2, C_1, C_Z, C_2, CP_1, CP_Z and CP_2 were analyzed.

B. Feature Extraction

All the labeled epochs for each electrode in the training sets were averaged to obtain two mean signals taken as representatives of their classes, one signal of P300 ($x_{P300}[n]$) and one signal of background EEG ($x_{EEG}[n]$). Then an EMD process (table I) was applied to each one of these signals to obtain a reference decomposition for each class:

$$x_{P300}[n] = \sum_{i=0}^{K} I_i^{P300}[n] \tag{1}$$

$$x_{EEG}[n] = \sum_{i=0}^{K} I_i^{EEG}[n], \tag{2}$$

TABLE I

EMD ALGORITHM AS REPORTED AN IMPLEMENTED IN [3]

1) Identify maxima and minima of signal, $x(t)$.
2) Interpolate between identified points to generate the superior wrap, $e_{max}(t)$ and the inferior wrap, $e_{min}(t)$
3) Compute the mean of the wraps, $m(t) = \frac{e_{min}(t)+e_{max}(t)}{2}$
4) Substract the IMF, $IMF_i = x(t) - m(t)$
5) Iterate again on residue, $m(t)$

where $I_i[n]$ is the $i-th$ IMF of the corresponfing signal.

A least squares fit of each EEG epoch to the IMF

$$x[n] \approx \sum_{i=0}^{K} b_i I_i[n] \tag{3}$$

was computed as the solution to the system

$$Ab = x, \tag{4}$$

where A is the matrix of IMF, b are the fit coefficients and x is the single ERP epoch:

$$A = \begin{bmatrix} I_0[0] & I_1[0] & \cdots & I_K[0] \\ \vdots & \vdots & & \vdots \\ I_0[N-1] & I_1[N-1] & \cdots & I_K[N-1] \end{bmatrix} \tag{5}$$

$$b = [b_0 \cdots b_K]^T, \tag{6}$$

$$x = [x[0] \cdots x[N-1]]. \tag{7}$$

The solution is given by the pseudoinverse of matrix A:

$$b = (A^T A)^{-1} A^T x \tag{8}$$

All the epochs in both classes and in both sets are fit with each base, producing b_+ and b_- features for classification.

The mean squares error of each fit was calculated to test the adjustment quality. A few epochs were badly approximated but they were included in the training set to increase method generalization, in other words, we include a bad adjusted training epoch that may classify a bad adjusted test epoch.

C. Pattern Recognition

A set of SVM with linear kernels (lin-SVM) were trained using 6-fold cross validation. A number of values for the SVM margin (C) were tested as part of the training to determine the performance of the classifier in terms of a ROC curve analysis [6].We use the library LIBSVM 2.81 [9] for the SVM implementation.

D. Performance and Validation

The proposed method was validated by estimations of sensitivity, specificity and accuracy. AUC was estimated using the Wilcoxon statistic. The mean values of every estimator and its standard deviation were calculated.

III. RESULTS

Fig. 1 shows the two representative signals and its IMF. The number of IMF isn't always the same for different signals, although we can calculate M IMF every time. Clearly, the IMF are different between classes.

Tables II y III show the mean values of the sensitivity, specificity, accuracy and AUC obtained for electrode C_Z. We can observe that the classifications shows a good performance for the Subject A data and an acceptable performance for Subject B data.

Fig. 2 show graphics of the AUC estimated for different values of the lin-SVM margin (C). Differences between rows and columns are obvious.

IV. DISCUSSION

The performance increment due to different feature sets isn't consistent across experiments, as we can see, there are differences between rows and columns even for the same subject. This variations suggest that a personalized analysis may be needed to achieve an optimal performance for each subject. The method shows a performance different to the chance classifier increasing the AUC to nearly the sixty percent, for some electrodes AUC is close to seventy percent. The differences between subject A and subject B may be consecuence of the SNR, and were expected since no frequency domain preprocessing was made.

The computations in the proposed method are only matrix operations, mostly multiplications, reason that suggest that its hardware implementation should be fast and easy, making our method a good candidate to real-time BCI applications. Our methodology is partially the same as a complete BCI system evaluation, since we focus in a method and evaluate its single trial performance.

V. CONCLUSIONS AND FUTURE WORK

A new method to detect P300 in a single EEG epoch was presented. The method extracts features by a least squaress fit of the epoch to a set of IMF, a lin-SVM classifier is used for ERP detection. The method is simple and takes only basic matrix operations, making it suitable to online use and hardware implementation.

Estimation of Sensitivity, Specificity, Accuracy and AUC were made, showing the performace for different feature sets. Inter- and Intra-subject differences are obvious and

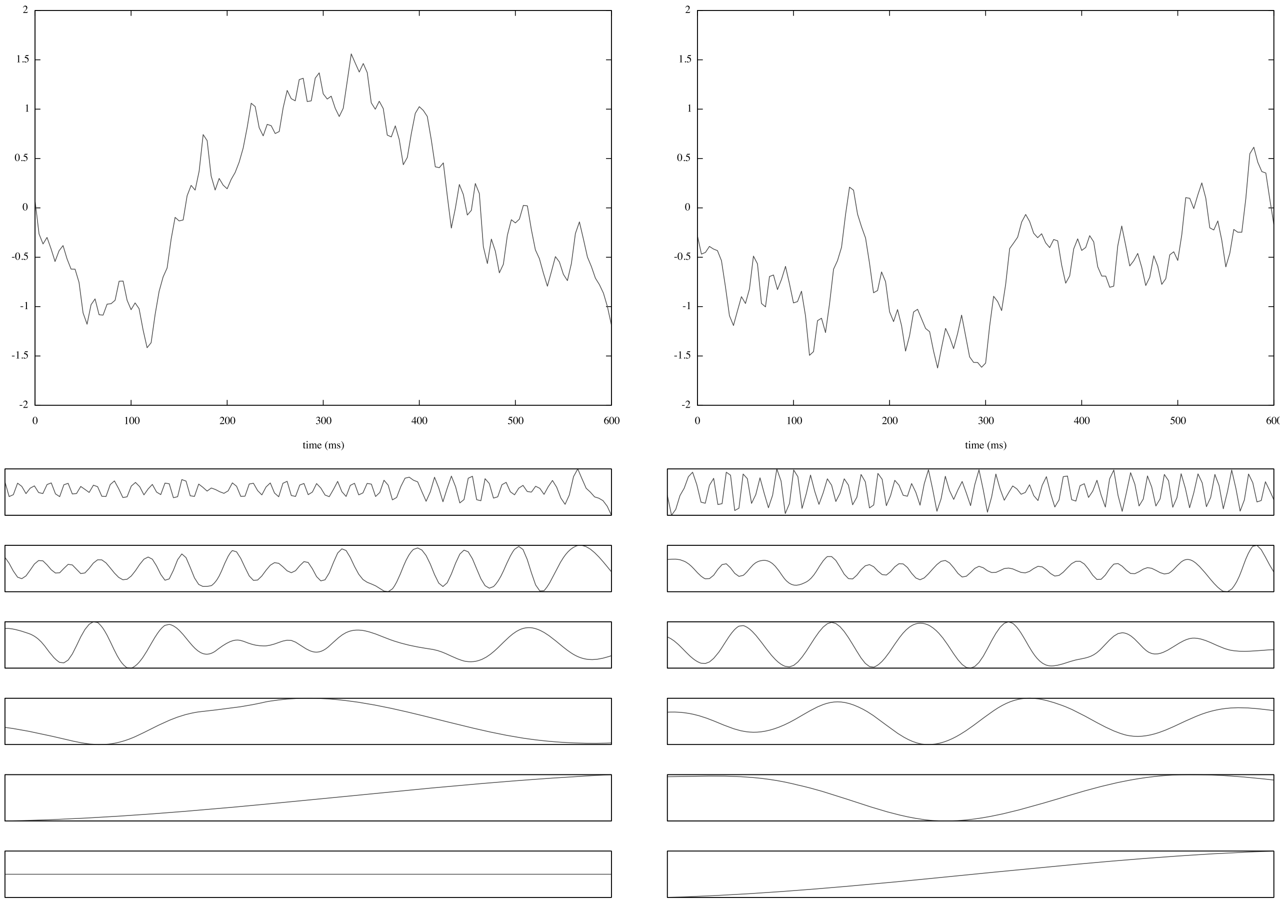

Fig. 1. Mean signals of each class (top) and their IMF (bottom). Subject B, rows, electrode C_Z. (Left: ERP epochs, Rigth: Background EEG) No axes are shown because the amplitude is irrelevant to the least squares fit. All the plots are from 0 to 600 ms.

TABLE II

SENSITIVITY, SPECIFICITY, ACCURACY AND AUC ESTIMATED FOR ELECTRODE C_Z, ROWS

Subject and Feature vector	Sensitivity	Specificity	Accuracy	AUC
A_{b_+}	0.616 ± 0.012	0.557 ± 0.009	0.567 ± 0.007	0.614 ± 0.004
A_{b_-}	0.610 ± 0.019	0.537 ± 0.017	0.549 ± 0.012	0.615 ± 0.004
$A_{[b_+,b_-]}$	0.596 ± 0.020	0.559 ± 0.011	0.565 ± 0.008	0.627 ± 0.002
B_{b_+}	0.474 ± 0.010	0.524 ± 0.012	0.515 ± 0.010	0.497 ± 0.007
B_{b_-}	0.551 ± 0.060	0.434 ± 0.021	0.454 ± 0.010	0.497 ± 0.011
$B_{[b_+,b_-]}$	0.486 ± 0.025	0.476 ± 0.009	0.477 ± 0.009	0.493 ± 0.005

TABLE III

SENSITIVITY, SPECIFICITY, ACCURACY AND AUC ESTIMATED FOR ELECTRODE C_Z, COLUMNS

Subject and Feature vector	Sensitivity	Specificity	Accuracy	AUC
A_{b_+}	0.608 ± 0.024	0.606 ± 0.009	0.606 ± 0.006	0.616 ± 0.003
A_{b_-}	0.598 ± 0.030	0.485 ± 0.015	0.504 ± 0.008	0.552 ± 0.003
$A_{[b_+,b_-]}$	0.560 ± 0.027	0.569 ± 0.017	0.568 ± 0.012	0.599 ± 0.007
B_{b_+}	0.528 ± 0.019	0.573 ± 0.020	0.565 ± 0.016	0.563 ± 0.004
B_{b_-}	0.676 ± 0.014	0.479 ± 0.009	0.512 ± 0.006	0.597 ± 0.012
$B_{[b_+,b_-]}$	0.580 ± 0.030	0.516 ± 0.019	0.527 ± 0.012	0.554 ± 0.010

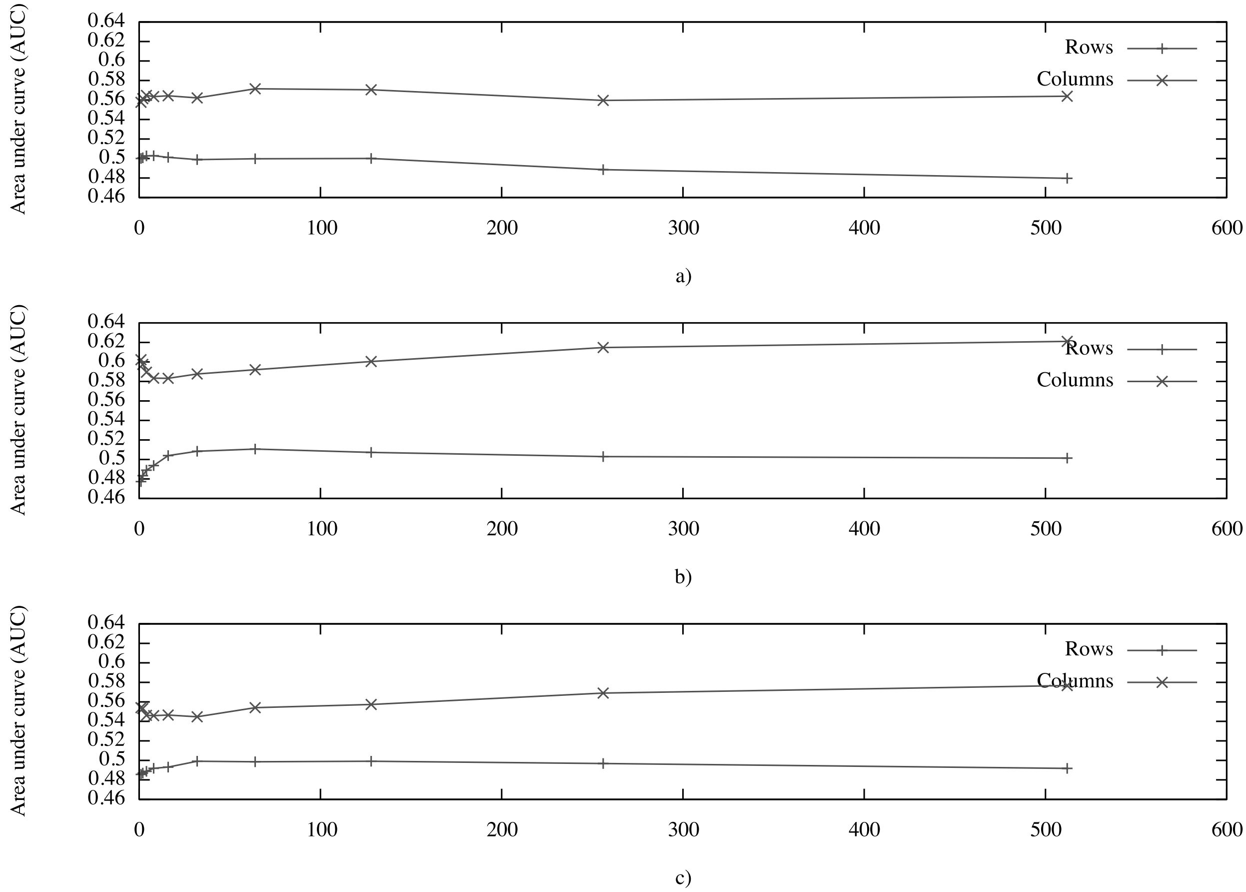

Fig. 2. AUC estimated for electrode C_Z, Subject B. From top to bottom: a) Features b_+, b) Features b_-, c) $[b_+, b_-]$

indicate the need to further explore our method under various conditions. AUC estimation is a good index of the classifier performance and it isn't skewed by the prevalence of classes.

We think that artifact rejection preprocessing, like Principal or Independent Component Analysis (PCA, ICA), or simply electrode feature concatenation may lead to a significative performance increase and make the method more robust across subjects. Future work will include electrode feature concatenation, artifact rejection preprocessing and application of SVM with radial basis function kernels. We will continue using AUC as an index of performance and complementary information in combination with sensibility, especificity and accuracy.

VI. ACKNOWLEDGMENTS

The authors gratefully acknowledge the contribution of Dr. Raquel Valdés Cristerna and Dr. Verónica Medina Bañuelos throughout the discussions and preparation of this work.

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