A VARIANCE-BASED APPROACH TO PERFORM SINGLE-TRIAL P300 DETECTION

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Abstract: *P300 is an event-related potential (ERP) recorded in scalp by means of electroencephalography (EEG), commonly used for developing brain-computer interfaces (BCI). One of the main challenges of using P300 is presented by its low signal-to-noise ratio (SNR), making its detection a dificult task. Grand averaging is a technique commonly used to overcome the low SNR. However, it requires longer EEG recording periods, which hardens the implementation of P300-based BCI. Hence, single-trial detection (STD) of such potential is desirable for this application. In this paper, we propose a method which uses metrics based on EEG variance together with logistic regression model to perform STD. The proposed method was tested in 24 subjects and showed mean accuracy of 76.1%, a promising result that is compatible/better with/than other ones found in literature.*

Keywords: *Electroencephalography (EEG), P300, single-trial detection, variance-based BCI, logistic regression.*

Introduction

The P300 potential is an event-related potential (ERP) that is recorded in the scalp, using electroencephalography (EEG). It arises as a response to sensory stimuli of interest (visual, auditory or somatosensory) that are presented in an infrequent way (*target signal*), alternating with other unimportant stimuli that happen frequently (*non-target signals*) [1].

This potential is registered most proeminently in the centro-parietal region and has a positive peak at around 300ms post-stimulus [1]. An example of a P300 signal with excellent signal-to-noise ratio (SNR) is shown in Figure 1 (blue line), where 120 epochs were used in the grand average calculation.

One of the main applications of P300 is the implementation of brain-computer interfaces (BCI), which are devices that can provide alternative ways to communicate and control the environment, using only brain waves [2].

In special, P300-based BCI is a useful alternative for patients whose motor impairment precludes the use of biosignals that have better SNR, such as eletromyography signals. This is the reason why P300-based BCI have been subject of intense research [1-3].

However, the major challenge in detecting P300 is the fact that spontaneous brain activity (spontaneous or background EEG) masks this potential, as illustrated in Figure 2, in which it is not possible to clearly differentiate *target* from *non-target* single epochs.

To overcome this obstacle, many signal processing techniques have been used to remove artifacts, increase the SNR and extract relevant features [4-6].

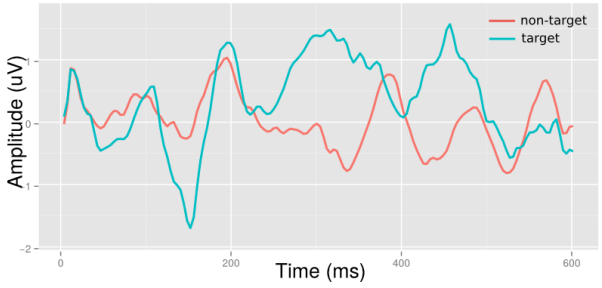

Figure 1: Example of P300 with good SNR.

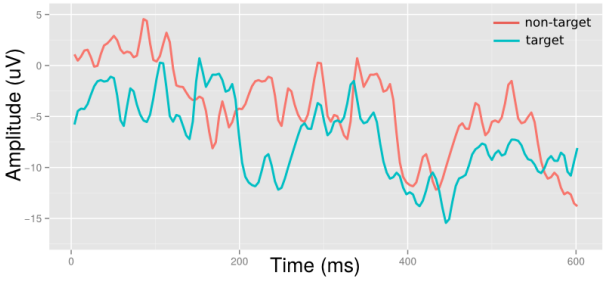

Figure 2: Example of *single-trial* P300 signal.

One of the most common signal processing techniques employed in the detection of P300 is the grand average [5].

This technique calculates the average of different EEG signal epochs, synchronized at the time of stimulation in order to reduce noise, specially, background EEG, and therefore increase SNR and classification rates [5].

However, this technique requires longer EEG recordings, hardening the use of BCI in practical applications [6]. Hence, the focus of this work is to propose a method capable of detecting *single-trial* P300, i.e., identify this potential from only one EEG epoch. This technique is further detailed in the next section.

Variance-based metrics definition

One of the main steps needed to perform ERP detection, such as P300, is extracting features that are able to distinguish the occurrence of the ERP. In this paper, the features extracted are derived from the method proposed by [6] and are based on the variance of EEG epochs which may or may not contain the P300.

An EEG epoch containing the P300 potential can be defined as:

$$x_0 = x_t + v, \tag{1}$$

where x_0 is the recorded EEG signal, with variance σ_0^2; x_t is the *target* signal (P300) with variance σ_t^2; and v is the background noise, considered to be random and stationary with variance σ_v^2.

Assuming that the *target* signal and the background noise are statistically independent, we can write:

$$\sigma_0^2 = \sigma_t^2 + \sigma_v^2 \tag{2}$$

Now, suppose that the grand average of k *target* epochs is calculated, being defined as x_{st}. Thus, the background noise variance will decrease to $\frac{\sigma_v^2}{k}$. Therefore, the grand average x_{st} can be described as:

$$x_{st} = \frac{1}{k}\sum_{i=1}^{k} x_{0_i} = \frac{1}{k}\sum_{i=1}^{k}(x_{t_i} + v_i), \tag{3}$$

where x_{0i} is the i-th recorded EEG epoch; x_{ti} is the i-th *target* epoch; and v_i denotes the background noise present in the i-th EEG epoch.

Assuming that the variances of v and x_t remain constant with time, the variance of x_{st} can be written as:

$$\sigma_{st}^2 = \sigma_t^2 + \frac{\sigma_v^2}{k} \tag{4}$$

Hence, by increasing the number of epochs used, the variance of the grand average (P300 estimate) approaches the variance of the *target* signal. To this extent, two variable transformations can be made from x_0 and x_{st}:

$$T_1 = \frac{x_{st} + x_0}{2} \tag{5}$$

$$T_2 = \frac{x_{st} - x_0}{2} \tag{6}$$

If x_0 is a *target* signal, the variances of transformations T_1 and T_2, derived from Equations 5 and 6, are given by:

$$var(T_1) = var\left(\frac{x_{st} + x_0}{2}\right) = \sigma_t^2 + \frac{(k+1)\sigma_v^2}{4k} \tag{7}$$

$$var(T_2) = var\left(\frac{x_{st} - x_0}{2}\right) = \frac{(k+1)\sigma_v^2}{4k} \tag{8}$$

In [6], a variance-based metrics, called D, was proposed from T_1 and T_2:

$$D = var(T_1) - var(T_2) = \sigma_t^2 \tag{9}$$

If x_0 is a *non-target* signal, the variances of the transformations T_1 and T_2 are:

$$var(T_1) = var(T_2) = \frac{(k+1)\sigma_v^2}{4k} \tag{10}$$

Therefore, D will be zero.

As Equations 9 and 10 show, the D metrics can be used to perform P300 detection, since it presents a theoretical value that is equal to σ_t for *target* and 0 for *non-target* signals.

Methodology

Database – The studied technique was applied to signals from the database provided by Ledesma-Ramirez *et al.* [7]. Subjects participated in the standard P300 elicitation protocol (*oddball paradigm*). Twenty-one symbols were presented for each volunter, arranged in a 6x6 matrix. Each row and each column of the matrix were intensified during 100ms, in a random order of intensification. If the row or column of the desired symbols was intensified, P300 elicitation was expected to occur [8].

The database contains signals from 24 subjects, with 5000 epochs per subject. These observations were divided into a training set, containing 20% of the total data (1000 observations) and a validation set, with the remaining 80% (4000 observations).

EEG signals were acquired with a sampling rate of 256Hz and band-filtered between 0.1 and 60Hz. The ground lead was connected to the right mastoid and the right earlobe was used as reference.

Pre-processing – For each stimulus presented to the user (row or column intensified), EEG epochs containing 600ms were extracted. These epochs were re-referenced using common average reference (CAR) [9], which is known to enhance the SNR for P300 identification.

CAR is calculated by subtracting the average of all EEG derivations from each individual derivation:

$$CAR(V_i) = V_i - \frac{1}{N}\sum_{n=0}^{N} V_n \tag{11}$$

where V_i is the derivation of interest; N is the number of derivations; and V_n is the n-th EEG derivation in the scalp.

After applying CAR, the baseline of the signals was removed, by subtraction the function with best linear fit from each corresponding epoch, to facilitate feature extraction.

Feature extraction – The training set was used to calculate the grand averages x_{st} of the *target-signal* for each EEG derivation, used as P300 templates.

Then, for each incoming *single-trial* signal x_0, D metrics was calculated using the template, for each analyzed derivation, constituting the feature vector employed to perform P300 detection.

Classification – The response variable established can assume only two classes: *target* and *non-target*. To describe the behavior of this kind of variable, logistic regression models are often used, being the response function, for multiple explanatory variables, defined as [10]:

$$E(y_i) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})}}, \qquad (12)$$

where $E(y_i)$ is the expected value of the response variable y_i, x_{ik} is the explanatory variable (feature), and β_k is the coefficient associated with the feature k.

Equation 12 models the relationship between y_i and the explanatory variables. Thus, the expected value can be used as a probability score in order to predict the outcome of the response variable [10].

D metrics values extracted from each derivation were used as inputs to the logistic regression model. The probabilities P_i generated by the model were used to classify each incoming signal as either a *target* (when $P_i > 0{,}5$) or a *non-target* (when $P_i < 0{,}5$) signal.

Results

Table 1 summarizes the results obtained in the detection of *single-trial* P300 signals, for the following performance parameters: Accuracy, area under the ROC curve (AUC), Sensitivity and Specificity. These results were calculated using 5 derivations (Fz, C4, Cz, C3 and P4) as inputs and are presented in terms of their medians and interquantile ranges (IQR).

Table 1: summary of results.

Parameter	Median	IQR
Accuracy	75.7%	6.8%
AUC	65.8	5.8
Sensitivity	74.0%	8.4%
Specificity	76.1%	6.8%

Figure 3 shows how Accuracy varies as the number of derivations used to classify the signals is increased from 1 to 10. This parameter seems to stabilize from 5 derivations onwards, with the median around 75.7%. The same observation can be made for AUC (Figure 4), Specificity (Figure 5) and Sensitivity (Figure 6), with median values remaining nearly stable, respectively, around 65.8, 74% and 76.1%.

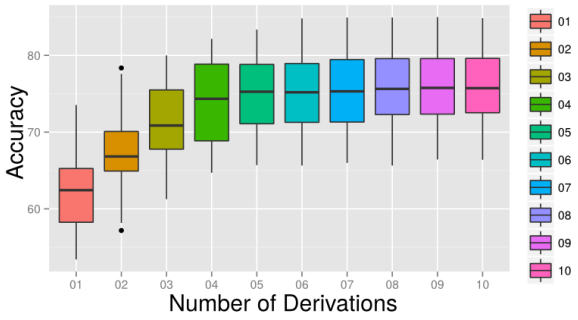

Figure 3: Accuracy versus number of derivations.

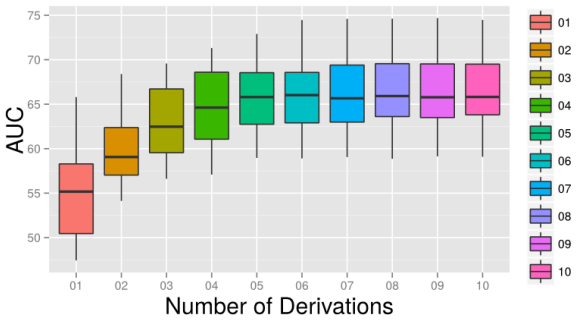

Figure 4: AUC versus number of derivations.

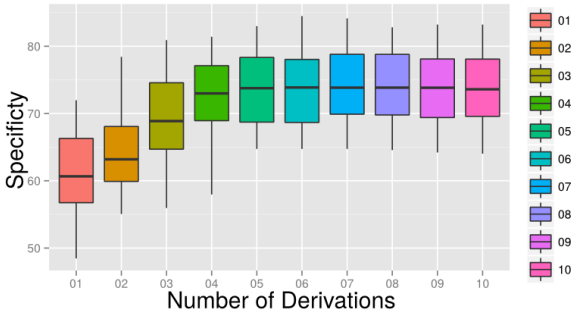

Figure 5: Specificity versus number of derivations.

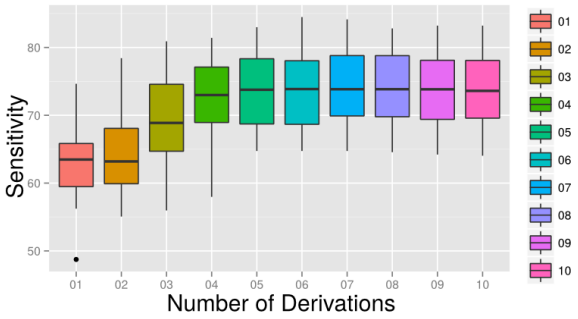

Figure 6: Sensitivity versus number of derivations.

Discussion

The results showed a clear improvement by increasing the number of derivations up to 5. Augmenting this value didn't result in relevant variation of performance parameters. This suggests that a small number of derivations is enough to perform *single-trial* P300 detection.

In Table 2, the method investigated in this paper is compared with recent literature works focused on *single-trial* P300 detection. As it can be noted, the performance of *D* method is comparable to the literature results.

Table 2: Comparison of results.

Reference	Subjects	Mean Accuracy
This work	**24**	**76.1 %**
Li 2009 [11]	1	76.7 %
Li 2012 [12]	5	84.8 %
Morales 2014 [13]	27	61.2 %
Xie 2014 [14]	8	85.7 %
Magee 2015 [15]	3	76.4 %

Particularly, it is worth noting that the proposed method was validated with a number of subjects that is far greater than the methods with superior performance, which indicates the strength of the proposed technique - associating variance-based criteria and logistic regression model - , meaning that it is robust to the highly variable P300 waveform. In comparison with the work that used a similar number of subjects [13], the evaluated method obtained better results.

Conclusion

In this paper, a variance-based metrics was combined with a logistic regression model to perform *single-trial* P300 detection. The proposed method obtained a mean accuracy of 76.1%, being tested on 24 subjects. These results are similar to the most recently reported in the literature, which indicates a promising tool for *single-trial* P300 detection.

We suggest that the proposed method can be applied to different ERP, other than P300, since its theoretical assumptions are based only on the generic model of the response to sensory/cognitive stimulation, masked by random additive noise (ERP generation model).

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References

[1] Allison BZ, Pineda JA. ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2003; 11(2): 110-113.

[2] Wolpaw J et al. Brain-computer interfaces for communication and control. Clinical Neurophysiology. 2002; 113(6):167–791.

[3] McFarland DJ et al. The P300-based brain computer interface (BCI): Effects of stimulus rate. Clinical Neurophysiology. 2011, 122(4): 731-737.

[4] Mason, SG, Birch, GE. A general framework for brain-computer interface design." IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2003, 11(1): 70-85.

[5] Bashashati A et al. A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals. Journal of Neural Engineering. 2007; 4(2): R32.

[6] Li K et al. Single trial independent component analysis for p300 bci system. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2009. p-4035-4038.

[7] Ledesma-Ramirez C et al. An open-access P300 speller database. In: 4th International BCI Meeting; 2010.

[8] Viana SS, Batista DM, Melges, DB. Logistic Regression Models: Feature Selection for P300 Detection Improvement. In: XXIV Brazilian Congress on Biomedical Engineering – CBEB 2014. 2014. p. 979–982.

[9] Alhaddad MJ. Common average reference (car) improves p300 speller." International Journal of Engineering and Technology. 2012, 2(3) : 21.

[10] Myers RH et al. Generalized linear models: with applications in engineering and the sciences. 1st ed: John Wiley & Sons; 2012.

[11] Li K. Advanced signal processing techniques for single-trial electroencephalography signal classification for brain-computer interface applications [PHd dissertation].Tampa: University of South Florida; 2010.

[12] Li K et al. A new single trial p300 classification method. International Journal of E-Health and Medical Communications (IJEHMC). 2012. 3(4): 31-41.

[13] Morales C et al. Single trial p300 detection in children using expert knowledge and som. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2014. p. 3801–3804.

[14] Xie S et al. Single channel single trial p300 detection using extreme learning machine: Compared with bpnn and svm. In: IEEE. International Joint Conference on Neural Networks. 2014. p. 544–549.

[15] Magee, R.; Givigi, S. A genetic algorithm for single-trial p300 detection with a low-cost eeg headset. In: Annual IEEE Internationa.Systems Conference. 2015. p. 230–234.