*Article*

# Oriented Gradient Histogram applied to P300 Detection

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Academic Editor: name

Version December 13, 2017 submitted Typeset by LaTeX

**Abstract:** EL OBJETIVO DE ESTE PAPER, EL HILO CONDUCTOR, ES DEMOSTRAR QUE ESTE METODO QUE ESTA BASADO EN LA ESTRUCTURA DE LA SENIAL SE PUEDE UTILIZAR TAMBIEN PARA IDENTIFICAR EVENTOS TRANSIENTES COMO EL P300, Y QUE CON ESO SE PUEDE IMPLEMENTAR UN SPELLER DE P300. The analysis of Electroencephalographic (EEG) signals is of ulterior importance to elucidate patterns that could improve the implementation of Brain Computer Interfaces (BCI). These systems are meant to provide alternative pathways to transmit volitional information which could potentially enhance the quality of life of patients affected by neurodegenerative disorders or improve Human Computer Interaction systems. Of particular interests are those which are based on the recognition of Event-Related Potentials (ERP) because they can be elicited by external stimuli and used to implement spellers, to control external devices or even avatars in virtual reality environments. This work mimics what electroencephalographers have been doing clinically, visually inspecting and categorizing phenomena within the EEG by the extraction of features from the images of the plots of the signals. It also aims to provide a framework to analyze, characterize and classify EEG signals, with a focus on the P300, an ERP elicited by the oddball paradigm of rare events. The validity of the method is shown by offline processing a public dataset of Amyotrophic Lateral Sclerosis (ALS) patients and an own dataset for healthy subjects.

**Keywords:** EEG; BCI; P300; ALS; NBNN; HOG; SIFT

## 0. Introduction

Although recent advances in neuroimagining techniques (particularly radio-nuclear and radiological scanning methods) [1] have diminished the prospects of the traditional Electroencephalography (EEG), the advent and development of digitalized devices has pressed for a revamping of this hundred years old technology. Their versatility, ease of use, temporal resolution, ease of development and fabrication, and its proliferation as consumer devices, are pushing EEG to become the de-facto non invasive portable or ambulatory method to access and harness brain information [2]

A key contribution to this expansion has been the field of Brain Computer Interfaces (BCI) [3] which is the pursuit of the development of a new channel of communication particularly aimed to persons affected by neurodegenerative diseases.

One noteworthy aspect of this novel communication channel is the ability to volitionally transmit information from the Central Nervous System (CNS) to a computer device and from there use that information to control a wheelchair [4], as input to a speller application [5], in a Virtual Reality environment [6] or as aiding tool in a rehabilitation procedure [7]. The holly grail of BCI is to implement a new complete and alternative pathway to restore lost locomotion [3].

EEG signals are remarkably complex and have been characterized as a multichannel non-stationary stochastic process. Additionally, they have high variability between different subjects and even between different moments for the same subject, requiring adaptive and co-adaptive calibration and learning procedures [8]. Hence, this imposes an outstanding challenge that is necessary to overcome in order to extract information from raw EEG signals.

Moreover, EEG markers [8] that can be used to volitionally transmit information are limited, and each one of them has a particular combination of appropriate methods to decode them. Inevitably, it is necessary to implement distinct and specialized algorithmic methods, to filter the signal, enhance its Signal to Noise Ratio (SNR), and try to determine some meaning out of it.

BCI has gained mainstream public awareness with worldwide challenge competitions like Cybathlon [9] and even been broadcasted during the inauguration ceremony of the 2014 Soccer World Cup. New developments have overcome the out-of-the-lab high-bar and they are starting to be used in real world environments [10]. However, they still lack the necessary robustness, and its performance is well behind any other method of human computer interaction, including any kind of detection of residual muscular movement [8].

In [11], authors introduce a method for classification of rhythmic EEG events like Visual Occipital Alpha Waves [12] and Motor Imagery rolandic central $\mu$ rhythms [13] using gradient histograms orientations. Inspired in that work, we proposed a novel application of the developed method to classify and describe transient events, particularly the P300 Event Related Potential. Its validity is verified by processing offline data for ALS patients and for healthy subjects. The proposed approach is based on the morphological analysis of the shape of the EEG signal [14,15] and it was built by mimicking what traditionally electroencephalographers have been performing for almost a century: visually inspecting raw signal plots [13].

This paper reports a method to, (1) classify P300 signals based on the identification of their structure in the shape domain using histograms of oriented gradients extracted from the image of signal plots, and (2) describe the way in which this classification can be used to implement an offline P300-based BCI Speller application using two public datasets.

This article unfolds as follows: in Section 1.1 the Feature Extraction based on Histogram of Gradients of the Signal Plot method is explained. Section **??** and 1.1.1 describe the processing pipeline. Section 1.1.4 clarifies how the image of the signal plot is constructed whereas Section 1.1.2 describes in detail the feature extraction procedure. Section 1.1.3 presents the classification algorithm based on Naive Bayes Nearest Neighbor (NBNN) [16] and the final Section shows results and discussion where we expose our remarks, conclusions and future work.

## 1. Materials and Methods

The P300 [17,18] is a positive deflection of the EEG signal which occurs around 300 ms after the onset of a rare and deviant stimulus that the subject is expected to attend. It is produced under the oddball paradigm [3] and it is consistent across different subjects. It has a lower amplitude ($\pm 5 \mu V$) compared to basal EEG activity, reaching a SNR of around $-15$ db estimated based on the amplitude of the P300 response signal divided by the standard deviation of the background EEG activity [19]. This signal can be used to implement a speller application by means of a Speller Matrix [17]. Fig. 1 shows an example of the Speller Matrix used in the OpenVibe Open Source software [20], where the flashings of rows and columns provide the deviant stimulus required to elicit this physiological response. Each time a row or column that contains the desired letter flashes, the corresponding synchronized EEG signal should also contain the P300 signature and by detecting it, the selected letter can be identified.


(a) Row flash. (b) Column flash.

**Figure 1.** Example of a Speller Matrix. Rows and columns flash intermittently in random permutations.

### *1.1. Feature Extraction based on Histogram of Gradients of the Signal Plot*

The underlying idea of this method is to generate templates for the signal [11], based on the image plot. Hence, the first step is the signal transformation into a temporary binary image.

#### 1.1.1. Processing Pipeline

- **Preprocessing**: The preprocessing stage consists of the enhancement of the SNR of the P300 pattern above the level of basal EEG. The processing pipeline starts by applying a notch filter to the raw signal, a 4th degree 10 Hz lowpass Butterworth filter and finally a decimation with a Finite Impulse Response (FIR) filter of order 30 from the original sampling frequency down to 16 Hz [21].
- **Artefact Removal**: The EEG signal matrix is processed on a channel by channel basis. For every 12 flashing stimuli, i.e. one complete sequence of intensification of each of the 6 rows plus the 6 columns, a basic artefact elimination procedure is implemented by removing the entire sequence when any signal deviates above/bellow $\pm 70 \mu V$.
- **Segmentation**: For each of the 12 stimuli, a window of 1 second of the multichannel signal is extracted, starting from the stimulus onset, corresponding to each row/column intensification. Two of these segments should contain the P300 ERP signature time-locked to the flashing stimulus, one for the row, and one for the column.
- **Signal Averaging**: The P300 ERP is deeply buried under background EEG so the traditional approach to identify it is by point-to-point averaging the time-locked stacked signal segments. Hence the values which are not related to, and not time-locked to the onset of the stimulus are canceled out [22].

This last step determines the operation of any P300 Speller. In order to obtain an improved signal in terms of its SNR, repetitions of the sequence of row/column intensification are necessary. And, at the same time, as long as more repetitions are needed, the ability to transfer information faster is diminished, so there is a trade-off that must be acutely determined.

#### 1.1.2. Feature Extraction: Histogram of Oriented Gradients

On the generated image, a keypoint **kp** is placed on a pixel $(x_{kp}, y_{kp})$ over the image plot and a window around the keypoint is considered. A local image patch of size $S_p \times S_p$ is constructed by dividing the window in 16 blocks of size $3s$ each one, where $s$ is the scale of the local patch and it is an input parameter of the algorithm. It is arranged in a $4 \times 4$ grid and the pixel $\mathbf{kp}$ is the patch center, then $S_p = 4.3s$ pixels.

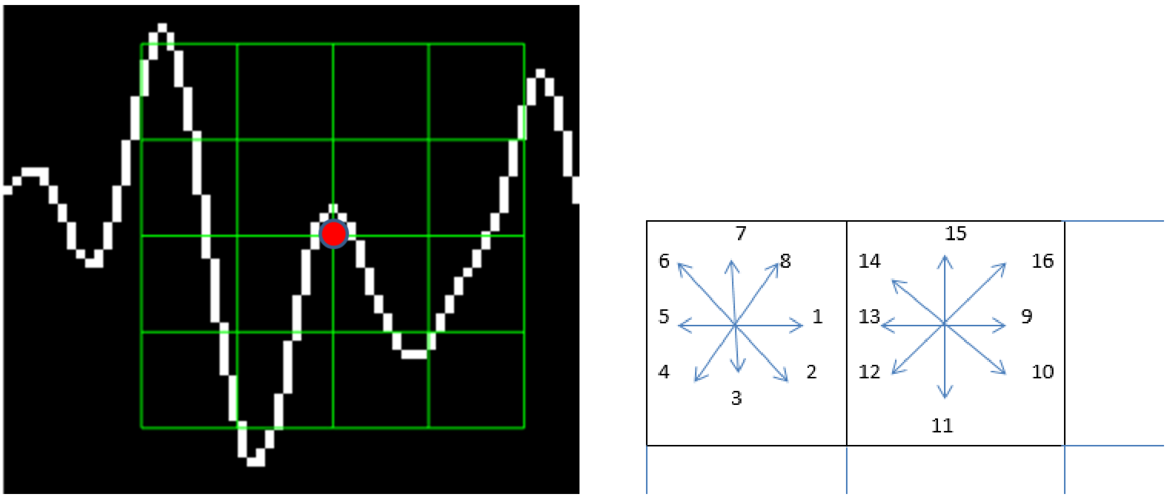
A local representation of the shape of the signal within the patch can be described by obtaining the gradient orientations on each of the 16 blocks and creating a histogram of gradients. This technique is based on Lowe's SIFT [24] method, and it is biomimetically inspired in how the visual cortex detects shapes by analyzing orientations. In order to calculate the histogram, the interval $[0 - 360]$ of possible angles is divided in 8 bins, each one at 45 degrees.

For each spacial bin $i, j = \{1, 2, 3, 4\}$, corresponding to the indexes of each block $B_{i,j}$, the orientations are accumulated in a 3-dimensional histogram $h$ through the following equation:

$$h(\theta, i, j) = 3s \sum_{\mathbf{x} \in B_{i,j}} w_{\text{ang}}(\angle J(\mathbf{x}) - \theta)\, w_{ij}\left(\frac{\mathbf{x} - \mathbf{kp}}{3s}\right) |J(\mathbf{x})| \tag{1}$$

where $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$, $i, j \in \{1, 2, 3, 4\}$, $|J(\mathbf{x})|$ is the norm of the gradient vector found at each block of the patch using finite differences, $\angle J(\mathbf{x})$ is the angle of the gradient vector, $\theta$ is the angle bin, $\mathbf{x}$ is a pixel from the $i, j$-block $B_{i,j}$ and $w_{\text{ang}}(\cdot)$ and $w_{ij}(\cdot)$ are linear interpolation functions used by Lowe and Vedaldi et al. in [24,25]. Lastly, the fixed value of 3 is a magnification factor which corresponds to the number of pixels per each block when $s = 1$. As the patch has 16 blocks and 8 bin angles are considered, a descriptor of 128 dimension is obtained. It can be observed that in each step, the histogram is computed by multiplying by $|J(\mathbf{x})|$ , so the method considers both, the magnitude and the orientation of the gradient vector.

Fig. 2 shows an example of a patch and a scheme of the histogram computation. Fig. 2(a) is a plot of the signal and the patch centered in the keypoint. In Fig. 2(b) the possible orientations on each patch are illustrated. They form the corresponding $\mathbf{kp}$-descriptor of 128 coordinates. The first two blocks are shown. Following this procedure for every assigned keypoint, we obtain $N_{kp}$ descriptors.




(a) Plot of the signal, a keypoint and the corresponding patch.

(b) Orientations on two blocks of the patch.

**Figure 2.** Example of a patch and a scheme of the orientation's histogram computation.

### 1.1.3. Speller Matrix letter Identification

The aim is to identify the selected letter from the matrix. Previously, during training phase, two descriptors are extracted from averaged signal segments which correspond to the letter where the user was supposed to be focusing onto. These descriptors are the P300 templates which are grouped in a template set called $T$. Segments corresponding to rows are labeled 1-6, whereas those corresponding to columns are labeled 7-12. The process has the following steps:

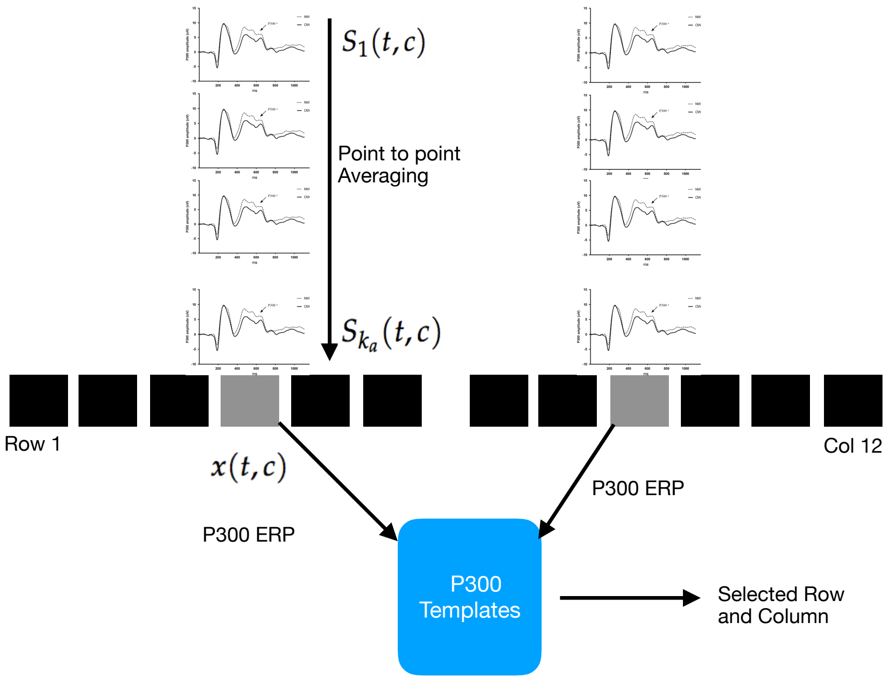



**Figure 3.** Single trial segments are averaged for the 6 rows and 6 columns.

1. Highlight randomly the rows and columns from the matrix. There is one row and one column that should match the letter selected by the subject.
2. Repeat item 1 $k_a$ times, obtaining the single trial segments $S_1(t,c),\dots,S_{k_a}(t,c)$, where the variables $t$ and $c$ correspond to time and chanel, respectively. The parameter $k_a$ is the number of repetitions and it is an input parameter of the algorithm.
3. Compute

$$x(t,c) = \frac{1}{k_a}\sum_{i=1}^{k_a} S_i(t,c) \tag{2}$$

4. Plot the signal $x(t,c)$, according Section 1.1.4.
5. Obtain the descriptor from the image of the signal plot of $x(t,c)$ in accordance to the method described in Section 1.1.2, $d^r_1,\dots,d^r_6$ for rows and $d^c_7,\dots,d^c_{12}$ for columns.
6. Match to the Template $T$ by computing

$$\hat{r} = \arg\min_{u\in\{1,\dots,6\}} \sum_{q\in NN_T(d^r_u)} \|q - d^r_u\|^2 \tag{3}$$

and

$$\hat{c} = \arg\min_{u\in\{7,\dots,12\}} \sum_{q\in NN_T(d^c_u)} \|q - d^c_u\|^2 \tag{4}$$

where $NN_T(d^l_u),\ l = r,c$ is the set of the $k$ nearest neighbors to $d^l_u,\ l = r,c$ and $q$ is a template descriptor that belongs to $NN_T(d^l_u),\ l = r,c$. By computing the aforementioned equations, the letter of the matrix can be determined from the intersection of the row $\hat{r}$ and column $\hat{c}$.

Figure 3 shows a schema of this process.

#### 1.1.4. Signal Plotting

Averaged signal segments are scaled and standardized by

$$\tilde{x}(t,c) = \left\lfloor \gamma \cdot \frac{(x(t,c) - \bar{x}(c))}{\sigma(c)} \right\rfloor \tag{5}$$

where $\gamma$ is the image scale, $t$ is time and $x(t,c)$ is the point-to-point averaged EEG matrix for time $t$ and for channel $c$. Lastly, $\bar{x}(c)$ and $\sigma(c)$ are the mean and standard deviation of $x$.

Consequently, the image is constructed by placing the sample points according to

$$I(z_1, z_2) = \begin{cases} 255 & \text{if } z_1 = \gamma \cdot t; z_2 = \tilde{x}(t,c) + z(c) \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where $z_1$ and $z_2$ iterate over the width (based on the length of the signal segment) and height (based on the peak-to-peak amplitude) of the newly created image. The function $z(c)$ is the *zerolevel* which is the location on the image where the signal's zero value should be located in order to fit the entire signal within the image:

$$z(c) = \left\lfloor \frac{\max \tilde{x}(t,c) - \min \tilde{x}(t,c)}{2} \right\rfloor - \left\lfloor \frac{\max \tilde{x}(t,c) + \min \tilde{x}(t,c)}{2} \right\rfloor \tag{7}$$

In order to complete the plot from the pixels, the Bresenham [11,23] algorithm is used to interpolate straight lines between each pair of consecutive pixels.

### *1.2. Experimental Protocol*

To verify the validity of the proposed framework and method, the public dataset 008-2014 [26] published on the BNCI-Horizon website [27] by IRCCS Fondazione Santa Lucia, is used. Additionally, an own dataset with the same experimental conditions is generated. Both of them are utilized to perform an offline BCI Simulation to decode the spelled words from the provided signals.

The algorithm is implemented using VLFeat [25] Computer Vision libraries on MATLAB V2014a (Mathworks Inc., Natick, MA, USA).

In the following sections the characteristics of the datasets and parameters of the identification algorithm are described.

#### 1.2.1. P300 ALS Public Dataset

The experimental protocol used to generate this dataset is explained in [26] but can be summarized as follows: 8 subjects with confirmed diagnoses but on different stages of ALS disease, were recruited and accepted to perform the experiments. The P300 detection task designed for this experiment consisted of spelling 7 words of 5 letters each, using the traditional P300 Speller Matrix [17]. The flashing of rows and columns provide the deviant stimulus required to elicit this physiological response. The first 3 words are used for training and the remaining 4 words, for testing with visual feedback. A trial, as defined by the BCI2000 platform [28], is every attempt to select a letter from the speller. It is composed of signal segments corresponding to $k_a = 10$ repetitions of flashes of 6 rows and $k_a = 10$ repetitions of flashes of 6 columns of the matrix, yielding 120 repetitions. Flashing of a row or a column is performed for 0.125 s, following by a resting period (i.e. Inter-stimulus interval) of the same length. After 120 repetitions an inter-trial pause is included before resuming with the following letter.

The recorded dataset was sampled at 256 Hz and it consisted of scalp EEG matrix for electrode channels Fz,Cz,Pz,Oz,P3,P4,PO7 and PO8, identified according to the 10-20 International System, for each one of the 8 subjects. The recording device was a research-oriented digital EEG device (g.Mobilab, g.Tec, Austria) and the data acquisition and stimuli delivery were handled by the BCI2000 open source software [28].

In order to asses and verify the identification of the P300 response, subjects are instructed to perform a copy-spelling task. They have to fix their attention to successive letters for copying a previously determined set of words, in contrast to a free-running operation of the speller where each user decides on its own what letter to choose.

#### 1.2.2. P300 for healthy subjects

We replicate the same experiment on healthy subjects using a wireless digital EEG device (g.Nautilus, g.Tec, Austria). The experimental conditions are the same as those used for the previous dataset, as detailed in section 1.2.1.

Participants are recruited voluntarily and the experiment is conducted anonymously in accordance with the declaration of Helsinki published by the World Health Organization. No monetary compensation is handed out and all participants agree and sign a written informed consent. All healthy subjects have normal or corrected-to normal vision and no history of neurological disorders. The experiment is performed with 20 subjects, 17 males, 3 females, average age 26.85 years, standard deviation 8.8 years, range 19-50 years.

Gel-based active electrodes (g.LADYbird, g.Tec, Austria) are used on the same locations Fz, Cz, P3, Pz, P4, PO7, PO8 and Oz. Reference is set to the right ear lobe and ground is preset as the AFz position. Sampling frequency is slightly different, and is set to 250 Hz, which is the closest possible to the one used with the other dataset.

#### 1.2.3. Parameters

The patch size is $S_P = 3s.4 \times 3s.4$ pixels, where $s$ is the scale of the local patch and it is an input parameter of the algorithm. The P300 event can have a span of 400 ms and its amplitude can reach $10\mu V$. Hence it is necessary to utilize a size patch $S_P$ that could capture an entire transient event. With this purpose in consideration, the $s$ value election is essential. We propose the equations 8 and 9 to compute the scale value in horizontal and vertical directions, respectively.

$$s_x = \frac{\lambda \cdot Fs}{4 \cdot 3} \cdot \gamma \tag{8}$$

$$s_y = \frac{\Delta \mu V}{4 \cdot 3} \cdot \gamma \tag{9}$$

where $\lambda$ is the length in seconds covered by the patch, $Fs$ is the sample frequency of the EEG signal (downsampled to 16 Hz) and $\Delta\mu V$ corresponds to the amplitude in microvolts that can be covered by the height of the patch. The geometric structure of the patch forces a squared configuration, then we discerned that by using $s = s_x = s_y = 3$ and $\gamma = 4$ the local patch and the descriptor can identify events of 9 $\mu V$ of amplitude, with a span of $\lambda = 0.56$ seconds. This also provides that 1 pixel represents $\frac{1}{\gamma} = \frac{1}{4}\mu V$ in the vertical direction and $\frac{1}{F_s \cdot \gamma} = \frac{1}{64}$ seconds in the horizontal direction. Finally, descriptors $\mathbf{kp}$ are located at $x_{kp} = 0.55 Fs.\gamma = 35$ and $y_{kp} = z(c)$ (see Eq. 7). In this way the whole transient event is captured. Figure 4 shows a patch of a signal plot covering the complete amplitude (vertical direction) and the complete span of the signal event (horizontal direction).

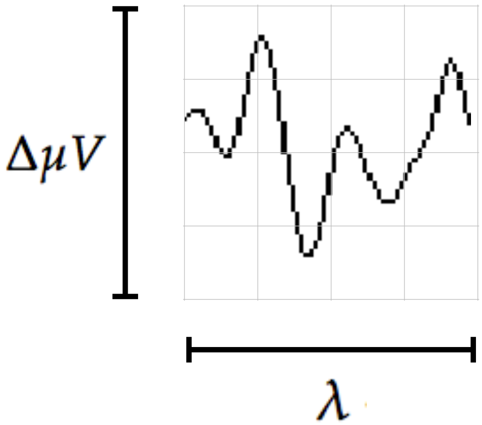



**Figure 4.** The scale of local patch is selected in order to capture the whole signal information. The vertical size $4 \cdot 3s_y$ of the patch is required to be long enough as to contain the signal $\Delta\mu V$, which is the peak-to-peak amplitude of the transient event. The horizontal size $4 \cdot 3s_x$ , on the other hand, needs to cover the entire duration in seconds of the transient signal event, $\lambda$.

## 2. Results and Discussion

Results are shown in Table 1 where the percentage of correctly spelled letters is calculated while performing an offline BCI Simulation for the public dataset of ALS patients. From the 7 words for each subject, the first 3 were used as training, and the remaining 4 for testing. The best performing channel is informed as well.

DRAFT: Traditionally P300 can be seen in this channel and this other channel. However, Wolpaw showed that the response may also arise in occipital channels as well. The authors of the original paper concluded that Cz was the best performing channel, more representative of the difference in amplitudes. However, in our approach occipital channels, PO8 and PO7 showed higher performances [7,10].

**Table 1.** Percentage of correctly predicted letters while performing an offline BCI Simulation for the best performing channel for each subject. Chance level is 2%.

| Participant | BPC | Performance |
|---|---|---|
| 1 | Cz | 35% |
| 2 | Fz | 85% |
| 3 | Cz | 25% |
| 4 | PO8 | 55% |
| 5 | PO7 | 40% |
| 6 | PO7 | 60% |
| 7 | PO8 | 80% |
| 8 | PO7 | 95% |

The ITR, or BTR, in the case of reactive BCIs [3] strongly depends on the amount of signal averaging required to transmit a valid and robust selection. The Performance curves (Fig. 5) show how the percentage of correctly identified letters depends on the number of repetitions that were used to obtain the averaged signal. For both datasets, the experimental protocol uses a very short ISI which has the potential to increase the ITR but at the same time is inversily proportional to the amplitude of the p300 response (i.e. harder to detect). As an unexpected consequence, 15 out of 20 subject reported high ocular tiredness by using this configuration.

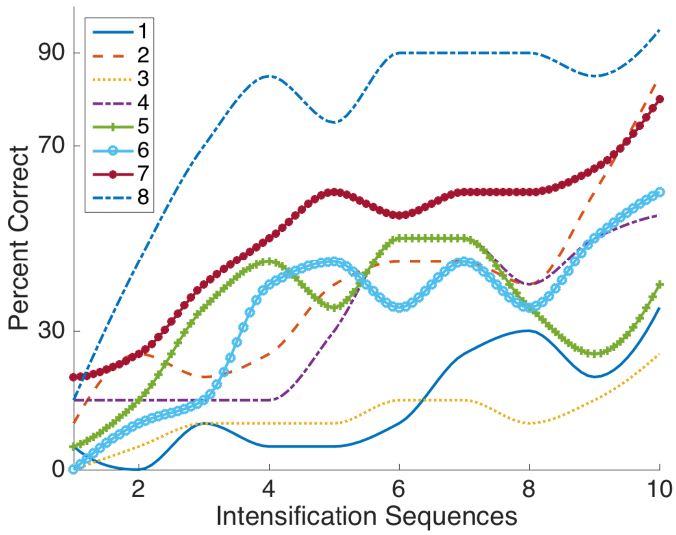



**Figure 5.** Performance curves for the eight subjects included in the published dataset. Three out of eight subjects achieved the necessary performance to implement a valid P300 speller.

We found that only by using the visual aspect of the P300 signal plot, for some subjects it was not possible to find templates that could allow the classification to reach a higher level. Moreover, as can be seen in the figure, as repetitions tend to 1, which will correspond to single trial letter identification, the performance suffers greatly as the signal plot is simple too complex to be used as template and the method is completely unable to find good matches PODRIA ACA MOSTRAR ADEMAS PLOTS DE SINGLE TRIAL PARA QUE VEAN QUE SON UN QUILOMBO.

UNA DE LAS RAZONES POR LA CUAL PODEMOS LLEGAR A ARGUMENTAR QUE NO FUIMOS MAS A FONDO CON EL TEMA ES QUE NO QUERIAMOS DISTORSIONAR DEMASIADO LA SENAL COMPLEJIZANDO EL ALGORITMO Y QUERIAMOS MANTENERNOS ENTRE LO MAS ESTANDAR POSIBLE (PUEDO CITAR MAS O MENOS QUE NUESTRO PROCESSING PIPELINE ES ESTANDARD).

We hypothesize that as subjects may have different latencies and amplitudes of the P300 signal [26], it may also be the case that the shape of the generated ERP may vary greatly in an intra-subject manner, thus the pattern could not be well generalized and a higher performance could not be reached (Fig. 6). It is known (REFERENCE) that the point-to-point averaging suffers from inter-trial variability (REFERENCIA A ESE PAPER Con ese nombre) due to latencies shifts. We tested a naive approach to verify if the morphological shape of the p300 can be stabilized by applying different shifts and we verified that there is a better performance when a correct resynchronization is applied. We also applied DTW but couldn't found a sustantial improvement.

Additionally we believe that our method suffers also from null signals.

ACA EL PUNTO PARA MOSTRAR ES QUE DE ALGUNA MANERA ESTAMOS COMO MOSTRANDO UN "SI SE PUEDE" DE UN TRABAJO QUE PUEDE CONTINUAR Y EXPANDIRSE. POR ESO LA IDEA DE MOSTRAR PUNTAS DE COSAS QUE VIMOS E HICIMOS, PERO SIN MOSTRAR RESULTADOS CONCRETOS.

Considering the amplitude variation of the p300 and its components, we proposed a conservative approach by standarizing the signal (which can have both effects, of reducing noise that were not reduced by the averaging procedure but at the same time it can reduce the amplitude of a significant p300 compoent). The standarization also provides another benefit which is sometimes neglected as unimportant. The variance of the averaged signal depends on the number of signals averaged. As this method analyze precisely the shape of the signal in the plot, which is very affected by the variance, the method will not be able to discriminate solely based on the underlying cognitive event, it will be confused by the number of signals that were used to calculate the averaged signal.

The SIFT method is invariant to the scale, but in order to allow our method to be also invariant to the amplitude of the signal we had to modify the geometry of the descriptor to remove the squared constrain.

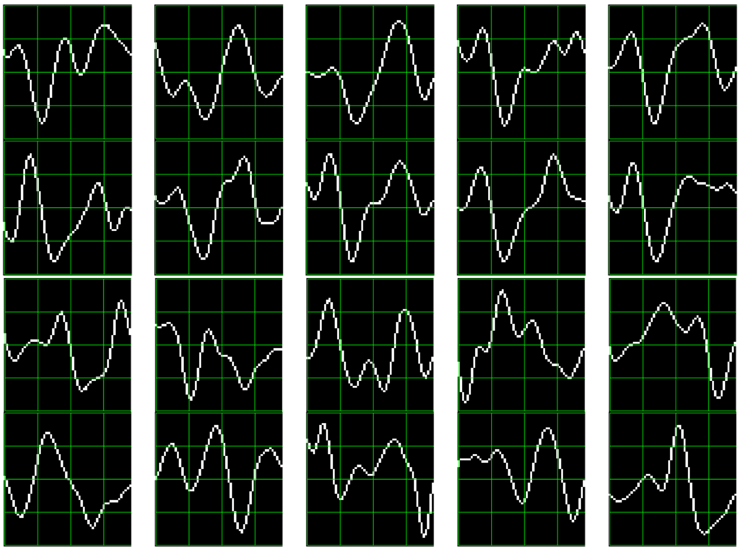


**Figure 6.** Ten P300 template patches found for subjects 8 (up) and 3(down). In coincidence with the performance results, the P300 signature is more clear and consistent for subject 8 (higher performance) while for subject 3 (lower performance) the characteristic pattern is much more difficult to perceive.

**Table 2.** Percentage of correctly predicted letters while performing an offline BCI Simulation for the best performing channel for each healthy subject. Chance level is 2%.

| Participant | BPC | Performance | |
|---|---|---|---|
| 1 | Cz | 0.7000 | 0.3500 |
| 1 | Cz | 0.1000 | 0.0500 |
| 1 | Cz | 0.1000 | 0.1000 |
| 1 | Cz | 0.1000 | 0.1500 |
| 1 | Cz | 0.1000 | 0.1000 |
| 1 | Cz | 0.5500 | 0.4000 |
| 1 | Cz | 0.1500 | 0.1000 |
| 1 | Cz | 0.4500 | 0.2000 |
| 1 | Cz | 0.3000 | 0.2000 |
| 1 | Cz | 0.2500 | 0.1500 |
| 1 | Cz | 0.5500 | 0.3000 |
| 1 | Cz | 0.3500 | 0.1000 |
| 1 | Cz | 0.3000 | 0.3500 |
| 1 | Cz | 0.5000 | 0.4000 |
| 1 | Cz | 0.3000 | 0.1500 |
| 1 | Cz | 0.3000 | 0.3000 |
| 1 | Cz | 0.3500 | 0.3500 |
| 1 | Cz | 0 | 0.0500 |
| 1 | Cz | 0.7000 | 0.5000 |
| 1 | Cz | 0.4000 | 0.3000 |

In Table 2 results obtained for the 20 healthy subjects is shown. The third column shows the results obtained by using the Krusienski feature and the SVM classifier. On the other hand, the fourth column shows the results obtained by the present method as described in previous sections. Subject 17 was used as control as he was instructed to count only the letters and to stare at the screen but not neglected row/column flashing.

## 3. Conclusion

A method to characterize and classify EEG signals where their characterization is transient in time-space, like the P300 ERP, has been presented.

The adaptive behaviour of the algorithm make it well suited when the shape of the pattern elicited by the P300 response does not conform to the predicted structure. This is due to the fact that the descriptors are directly based on how the signals behave in shape domain (i.e. *how actually they looked like*) for the training and calibration step, and they do not require any prior knowledge about the signal. In contrast, when the shape of the ERP response is not consistent across the same subject, this method would not be able to find the templates and speller performance could be penalized.

At the same time, by analyzing the generated descriptors, which map in a very detailed and synthetic structure the shape information contained within the patch, a metric about the consistency of the shape of the generated P300 response could also be derived. It may be worthy of further consideration to evaluate if there is any correlation between the lower performance obtained for some subjects and the characterization of their ALS stage.

We believe that the expanding and the understanding of this tool in order to automatically classify those patterns in EEG that are specifically identified by their shapes (e.g. K-Complex, Vertex Waves, Positive Occipital Sharp Transient [13]) is a prospect future work to be considered. We are currently working in unpublished material analyzing KComplex that may also provide assistance to physician or electroencephalographers to help them locate these EEG patterns particularly in long recording periods, frequent in sleep research.

Moreover, this method can be used as an alternate *BCI predictor* [8], i.e. to detect BCI illiteracy or to predict the achievable performance of a given method, or even as a tool for artefact removal (which is performed on many occasions by visually inspecting the signal).

**Acknowledgments:** This project was supported by the ITBACyT-15 funding program issued by ITBA University. The authors would like to thank Dr. Juliana Gambini for their insights and help with the detailed description of the histogram of gradients.

**Conflicts of Interest:** The authors declare that there is no conflict of interest regarding the publication of this article.

## Abbreviations

The following abbreviations are used in this manuscript:

EEG: Electroencephalography
BCI: Brain Computer Interfaces
SNR: Signal to Noise Ratio
CNS: Central Nervous System
ALS: Amyotrophic Lateral Sclerosis
ERP: Event-Related Potential
P300: Positive deflection of an Event-Related Potential which occurs 300 ms after onset of stimulus
ITR: Information Transfer Rate
BTR: Bit Transfer Rate
SIFT: Scale Invariant Feature Transform
NBNN: Naive Bayes Nearest Neighbor
HOG: Histogram Of Gradients

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