Histogram of Gradient Orientations of Signal Plots applied to P300 Detection

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ABSTRACT

The analysis of Electroencephalographic (EEG) signals is of ulterior importance for decoding 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 and other mental illness. 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 of healthy subjects.

Keywords: electroencephalography, brain-computer interfaces, P300, SIFT, amyotrophic lateral sclerosis, naive-bayes near neighbours, histogram of gradients

1 INTRODUCTION

Although recent advances in neuroimagining techniques, particularly radio-nuclear and radiological scanning methods (Schomer and Silva, 2010), have diminished the prospects of the traditional Electroencephalography (EEG), the advent and development of digitized devices has impelled 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 (De Vos and Debener, 2014).

A key contribution to this expansion has been the field of Brain Computer Interfaces (BCI) (Wolpaw and E., 2012) 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 transmit information from the Central Nervous System (CNS) to a computer device and from there use that information to control a wheelchair (Carlson and del R. Millan, 2013), as input to a speller application (Guger et al., 2009), in a Virtual Reality environment (Lotte et al., 2013) or as aiding tool in a rehabilitation procedure (Jure et al., 2016). The holly grail of BCI is to implement a new complete and alternative pathway to restore lost locomotion (Wolpaw and E., 2012).

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 (Clerc et al., 2016). Hence, this imposes an outstanding challenge that is necessary to overcome in order to extract information from raw EEG signals.

BCI has gained mainstream public awareness with worldwide challenge competitions like Cybathlon (Riener and Seward, 2014; Novak et al., 2018) 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 (Guger et al., 2017; Huggins et al., 2016). 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 (Clerc et al., 2016).

A few works have explored the idea of exploiting the signal waveform to analyze the EEG signal. In (Alvarado-González et al., 2016) an approach based on Slope Horizontal Chain Code is presented, whereas in (Yamaguchi et al., 2009) a similar procedure was implemented based on Mathematical Morphological Analysis. The seminal work of Bandt-Pompe Permutation Entropy (Berger et al., 2017) also explores succinctly this idea as a basis to establish the time series ordinal patterns. In the article (Ramele et al., 2016), the authors introduce a method for classification of rhythmic EEG events like Visual Occipital Alpha Waves and Motor Imagery Rolandic Central μ Rhythms using the histogram of gradient orientations of signal plots. Inspired in that work, we propose a novel application of the developed method to classify and describe transient events, particularly the P300 Event Related Potential. The proposed approach is based on the waveform analysis of the shape of the EEG signal, but using histogram of gradient orientations. The method is built by mimicking what traditionally electroencephalographers have been performing for almost a century as it is described in (Hartman, 2005): visually inspecting raw signal plots.

This paper reports a method to, (1) describe a procedure to capture the shape of a waveform of an ERP component, the P300, using histograms of gradient orientations extracted from images of signal plots, and (2) outline the way in which this procedure can be used to implement an offline P300-based BCI Speller application. Its validity is verified by offline processing two datasets, one of data from ALS patients and another one from data of healthy subjects.

This article unfolds as follows: Section 2.1 is dedicated to explain the Feature Extraction method based on Histogram of Gradient Orientations of the Signal Plot: Section 2.1.1 shows the preprocessing pipeline, Section 2.1.3 describes the image generation of the signal plot, Section 2.1.4 presents the feature extraction procedure while Section 2.1.5 introduces the whole Speller Matrix Letter Identification procedure including the classification algorithm based on Naive Bayes Nearest Neighbor (NBNN) (Boiman et al., 2008). In Section 2.2, the experimental protocol is expounded. Section 3 shows the results of applying the proposed technique. In the final Section 4 we expose our remarks, conclusions and future work.

2 MATERIALS AND METHODS

The P300 (Farwell and Donchin, 1988; Knuth et al., 2006) 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 (Wolpaw and E., 2012) 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 (Hu et al., 2010). This signal can be used to implement a speller application by means of a Speller Matrix (Farwell and Donchin, 1988). Fig. 1 shows an example of the Speller Matrix used in the OpenVibe open source software (Renard et al., 2010), where the flashes of rows and columns provide the deviant stimulus required to elicit this physiological response. Each time a row or a 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.

2.1 Feature Extraction from Signal Plots

In this section, the signal preprocessing, the method for generating images from signal plots, the feature extraction procedure and the Speller Matrix identification are described.

2.1.1 Preprocessing Pipeline

The data obtained by the capturing device is digitalized and a multichannel EEG signal is constructed, where rows are sample points and columns are channels (electrodes).

- **Signal Enhancement**: The preprocessing stage consists of the enhancement of the SNR of the P300 pattern above the level of basal EEG. The pipeline starts by applying a notch filter to the raw digital 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 (Krusienski et al., 2006).
- **Artifact Removal**: The multichannel EEG signal is processed on a channel by channel basis. For every complete sequence of 12 intensification of 6 rows and 6 columns, a basic artifact 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 intensifications, a window of $t_{max} = 1$ 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 (Liang and Bougrain, 2008).

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.

2.1.2 Ensemble Average

The procedure to obtain the point-to-point averaged signal goes as follows:

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 step 1 k_a times, obtaining the single trial segments $S_1(n,c),\ldots,S_{k_a}(n,c)$, of the EEG signal where the variables $n \in \{1,\ldots,n_{max}\}$ and $c \in \{1,2,\ldots,Ch\}$ correspond to sample points and channel, respectively. The parameter Ch is the number of available EEG channels whereas $n_{max} = F_s.t_{max}$ is the segment length and F_s is the sampling frequency. The parameter k_a is the number of repetitions of intensifications and it is an input parameter of the algorithm.
3. Compute the Ensemble Average by

$$x(n,c) = \frac{1}{k_a}\sum_{i=1}^{k_a} S_i(n,c), n \in \{1,\ldots,n_{max}\}, c \in \{1,\ldots,Ch\} \tag{1}$$

for each row and column on the Speller Matrix.

2.1.3 Signal Plotting

Averaged signal segments are standardized and scaled by

$$\tilde{x}(n,c) = \left\lfloor \gamma \cdot \frac{(x(n,c) - \bar{x}(c))}{\hat{\sigma}(c)} \right\rfloor,\ n \in \{1,\ldots,n_{max}\},\ c \in \{1,2,\ldots,Ch\} \tag{2}$$

where $\gamma > 0$ is an input parameter of the algorithm and it is related to the image scale. In addition, $x(n,c)$ is the point-to-point averaged multichannel EEG signal for the sample point n and for channel c. Lastly,

$$\bar{x}(c) = \frac{1}{n_{max}}\sum_{n=1}^{n_{max}} x(n,c)$$

and

$$\hat{\sigma}(c) = \Big(\frac{1}{n_{max}-1}\sum_{n=1}^{n_{max}} (x(n,c) - \bar{x}(c))^2\Big)^{\frac{1}{2}}$$

are the mean and estimated standard deviation of $x(n,c), n \in \{1,\ldots,n_{max}\}$, for each channel c.

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

$$I(z_1,z_2) = \begin{cases} 255 & \text{if } z_1 = \gamma \cdot n;\ z_2 = \tilde{x}(n,c) + z(c) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $(z_1,z_2) \in \mathbb{N} \times \mathbb{N}$ 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, $n \in \{1,\ldots,n_{max}\}$ and $c \in \{1,2,\ldots,Ch\}$. The values $z(c)$, $c \in \{1,2,\ldots,Ch\}$ are the location on the image where the signal's zero value has to be located in order to fit the entire signal within the image for each c:

$$z(c) = \left\lfloor \frac{\max_n \tilde{x}(n,c) - \min_n \tilde{x}(n,c)}{2} \right\rfloor - \left\lfloor \frac{\max_n \tilde{x}(n,c) + \min_n \tilde{x}(n,c)}{2} \right\rfloor \quad (4)$$

where the minimization and maximization are carried out for n varying between $1 \leq n \leq n_{max}$.

In order to complete the plot from the pixels, the Bresenham (Bresenham, 1965; Ramele et al., 2016) algorithm is used to interpolate straight lines between each pair of consecutive pixels.

2.1.4 Feature Extraction: Histogram of Gradient Orientations

On the generated image I, a keypoint $\mathbf{kp}$ 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 $S_p \times S_p$ pixels 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 4×4 grid and the pixel $\mathbf{kp}$ is the patch center, thus $S_p = 12s$ 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 (Lowe, 2004) method, and it is biomimetically inspired in how the visual cortex detects shapes by analyzing orientations (Edelman et al., 1997). In order to calculate the histogram, the interval $[0 - 360]$ of possible angles is divided in 8 bins, each one at 45 degrees.

Hence, for each spacial bin $i, j = \{0, 1, 2, 3\}$, corresponding to the indexes of each block $B_{i,j}$, the orientations are accumulated in a 3-dimensional histogram h through the following equation:

$$h(\theta, i, j) = 3s \sum_{\mathbf{p}} w_{\text{ang}}(\angle J(\mathbf{p}) - \theta)\, w_{ij} \left(\frac{\mathbf{p} - \mathbf{kp}}{3s} \right) |J(\mathbf{p})| \quad (5)$$

where $\mathbf{p}$ is a pixel from within the patch, θ is the angle bin with $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$, $|J(\mathbf{p})|$ is the norm of the gradient vector in the pixel $\mathbf{p}$ and it is computed using finite differences and $\angle J(\mathbf{p})$ is the angle of the gradient vector. The scalar $w_{\text{ang}}(\cdot)$ and vector $w_{ij}(\cdot)$ functions are linear interpolations used by Lowe (2004) and Vedaldi and Fulkerson (2010) to provide a weighting contribution to eight adjacent bins. They are calculated as

$$w_{ij}(\mathbf{v}) = w(v_x - x_i) w(v_y - y_i) \quad (6)$$

$$w_{\text{ang}}(\alpha) = \sum_k w\left(\frac{8\alpha}{2\pi} + 8r\right) \quad (7)$$

where x_i and y_i are the spatial bin centers located in $x_i, y_i = \{-\frac{3}{2}, -\frac{1}{2}, \frac{1}{2}, \frac{3}{2}\}$, $\mathbf{v} = (v_x, v_y)$ is a dummy vector variable and α a dummy scalar variable. On the other hand, r is an integer that can vary freely which allows the argument α to be unconstrained in terms of its values in radians. The interpolating function $w(\cdot)$ is defined as:

$$w(z) = \max(0, |z| - 1) \quad (8)$$

These binning functions conform a trilinear interpolation that has a combined effect of sharing the contribution of each oriented gradient between their eight adjacent bins in a tridimensional cube in the histogram space, and zero everywhere else.

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 feature called *descriptor* of 128 dimension is obtained.

Fig. 2 shows an example of a patch and a scheme of the histogram computation. In (A) a plot of the signal and the patch centered around the keypoint is shown. In (B) the possible orientations on each patch are illustrated. Only the upper-left four blocks are visible. The first eight orientations of the first block, are labeled from 1 to 8 clockwise. The orientations of the second block $B_{1,2}$ are labeled from 9 to 16. This labeling continues left-to-right, up-down until the eight orientations for all the sixteen blocks are assigned. They form the corresponding $\mathbf{kp}$-descriptor of 128 coordinates.

2.1.5 Speller Matrix letter Identification

The aim is to identify the selected letter from the matrix. Previously, during the 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. This set is constructed using the steps described in Section 2.1.2 and the steps A and B of the following algorithm. Segments corresponding to rows are labeled 1-6, whereas those corresponding to columns are labeled 7-12. The whole process has the following steps:

First highlight randomly the rows and columns from the matrix and obtain the Ensemble Average as detailed in steps 1,2 and 3 in Section 2.1.2.

- **Step A:** Plot the signals $x(n, c)$, $n \in \{1, \ldots, n_{max}\}$, $c \in \{1, \ldots, Ch\}$, according Section 2.1.3 in order to generate the images $I_1^{row}, \ldots, I_6^{row}$ and $I_7^{col}, \ldots, I_{12}^{col}$ for rows and columns, respectively.
- **Step B:** Obtain the descriptors $d_1^{row}, \ldots, d_6^{row}$ and $d_7^{col}, \ldots, d_{12}^{col}$ for rows and columns, respectively from $I_1^{row}, \ldots, I_6^{row}$ and $I_7^{col}, \ldots, I_{12}^{col}$ in accordance to the method described in Section 2.1.4.
- **Step C:** Match to the Template T by computing

$$\hat{row} = \arg \min_{u \in \{1,\ldots,6\}} \sum_{q \in NN_T(d_u^{row})} \left\| q - d_u^{row} \right\|^2 \tag{9}$$

and

$$\hat{col} = \arg \min_{u \in \{7,\ldots,12\}} \sum_{q \in NN_T(d_u^{col})} \left\| q - d_u^{col} \right\|^2 \tag{10}$$

where $NN_T(d_u^l),\ l \in \{row, col\}$ is the set of the k nearest neighbors to d_u^l and q is a template descriptor that belongs to it. This set is obtained by sorting all the elements in T based on the distances between them and d_u^l, choosing the k smaller. This algorithm is a modificaton of the k-NBNN algorithm (Boiman et al., 2008).

By computing the aforementioned equations, the letter of the matrix can be determined from the intersection of the row $\hat{row}$ and column $\hat{col}$. Figure 4 shows a scheme of this process.

2.2 Experimental Protocol

To verify the validity of the proposed framework and method, the public dataset 008-2014 (Riccio et al., 2013) published on the BNCI-Horizon website (Brunner et al., 2014) 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 (Vedaldi and Fulkerson, 2010) 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.

2.2.1 P300 ALS Public Dataset

The experimental protocol used to generate this dataset is explained in (Riccio et al., 2013) 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 Visual P300 detection task designed for this experiment consisted of spelling 7 words of 5 letters each, using the traditional P300 Speller Matrix (Farwell and Donchin, 1988). 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 (Schalk et al., 2004), 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 a scalp multichannel EEG signal 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 (Schalk et al., 2004).

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.

2.2.2 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 2.2.1.

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 8 subjects, 6 males, 2 females, 6 right-handed, 2 left-handed, average age 29.00 years, standard deviation 11.56 years, range 20-56 years.

EEG data is collected in a single recording session. Participants are seated in a comfortable chair, with their vision aligned to a computer screen located one meter in front of them. The handling and processing of the data and stimuli is conducted by the OpenVibe platform (Renard et al., 2010).

Gel-based active electrodes (g.LADYbird, g.Tec, Austria) are used on the same locations Fz, Cz, Pz, Oz, P3,P4, PO7 and PO8. 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.

2.2.3 Parameters

The patch size is $S_P = 12s \times 12s$ 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 $10\mu V$ (Rao, 2013). 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 11 and 12 to compute the scale value in horizontal and vertical directions, respectively.

$$s_x = \frac{\lambda \cdot Fs}{12} \cdot \gamma \tag{11}$$

$$s_y = \frac{\Delta \mu V}{12} \cdot \gamma \tag{12}$$

where λ is the length in seconds covered by the patch, Fs is the sampling 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 μV of amplitude, with a span of $\lambda = 0.56$ seconds. This also provides that 1 pixel represents $\frac{1}{\gamma} = \frac{1}{4}\mu V$ on the vertical direction and $\frac{1}{Fs.\gamma} = \frac{1}{64}$ seconds on the horizontal direction. Descriptors $\mathbf{kp}$ are located at $(x_{kp}, y_{kp}) = (0.55Fs.\gamma, z(c)) = (35, z(c))$ for the corresponding channel c (see Eq. 4). In this way the whole transient event is captured. Figure 5 shows a patch of a signal plot covering the complete amplitude (vertical direction) and the complete span of the signal event (horizontal direction).

Lastly, the number of channels Ch is equal to 8 for both datasets, and the number of intensification sequences k_a is statically assigned to 10. The parameter k used to construct the set $NN_T(d_u^l),\ \ l \in \{row, col\}$ is assigned to $k = 7$, which was found empirically to achieve better results. In addition, the norm used on Equations 9 and 10 is the cosine norm, and descriptors are normalized to $[-1, 1]$.

3 RESULTS

Table 1 shows the results of applying the algorithm to the subjects of the public dataset of ALS patients (Riccio et al., 2013). The percentage of correctly spelled letters is calculated while performing an offline BCI Simulation. From the seven words for each subject, the first three are used as training, and the remaining four for testing. The best performing channel is informed as well. The chance level is 2%. It can be observed that the best performance of the letter identification method is reached in various channels depending on the subject on study.

The Information Transfer Rate (ITR), or Bit Transfer Rate (BTR), in the case of reactive BCIs (Wolpaw and E., 2012) depends on the amount of signal averaging required to transmit a valid and robust selection. Fig. 6 shows the performance curves for varying intensification sequences. It can be noticed that the percentage of correctly identified letters depends on the number of intensification sequences k_a that are used to obtain the averaged signal. Moreover, when the number of intensification sequences tend to 1, which corresponds to single-trial letter identification, the performance is reduced. As mentioned before, the SNR of the single-trial P300 is very low and the shape of its P300 component is not very well defined.

In Table 2 results obtained for 8 healthy subjects are shown. The obtained performance were slightly inferior than those obtained for ALS patients but well above chance level.

Occipital Channels

The P300 ERP consists of two overlapping components: the P3a and P3b, the former with frontocentral distribution while the later stronger on centroparietal region (Polich, 2007). Hence, the standard practice is to find the stronger response on the central channel Cz (Riccio et al., 2013). However, Krusienski et al. (2006) show that the response may also arise in occipital regions. We found that by analyzing only the waveforms, occipital channels PO8 and PO7 show higher performances for some subjects.

Stability of the P300 shape

As subjects have varying *latencies* and *amplitudes* of their P300 components, they also have a varying stability of the *shape* of the generated ERP (Nam et al., 2010). Figure 7 shows the P300 templates patches for patients 8 and 3 from the dataset of ALS patients. It can be discerned that in coincidence with the performance results, the P300 signature is more clear and consistent for subject 8 (A) while for subject 3 (B) the characteristic pattern is more difficult to perceive.

Additionally, the stability of the P300 component waveform has been extensively studied in patients with ALS (Eric W. Sellers and Emanuel Donchin, 2006; Madarame et al., 2008; Nijboer and Broermann, 2009; Mak et al., 2012; McCane et al., 2015) where it was found that these patients have a stable P300 component, which were also sustained across different sessions. In line with these results we do not find evidence of a difference in terms of the performance obtained for the group of patients with ALS and the healthy group of volunteers. Particularly, the best performance is obtained for a subject from the ALS dataset for which, based on visual observation, the shape of they P300 component is consistently identified.

Descriptor Space and classification method

It is important to remark that when applied to binary images obtained from signal plots, the feature extraction method described in Section 2.1.4 generates sparse descriptors. Under this subspace we found that using the cosine metric yielded a significant improvement on the performance. On the other hand, the unary classification scheme based on the NBNN algorithm proved very beneficial for the P300 Speller Matrix. This is due to the fact that this approach solves the unbalance dataset problem which is inherent to the oddball paradigm (Tibon and Levy, 2015).

4 DISCUSSION

Among other applications of Brain Computer Interfaces, the goal of the entire discipline is to provide communication assistance to people affected by neuro-degenerative diseases, who are the most likely population to benefit from BCI systems and EEG processing and analysis.

In this work, a method to detect transient P300 components from EEG signals based on their waveform characterization in digital time-space, is presented. Additionally, its validity is evaluated using a public dataset of ALS patients and an own dataset of healthy subjects.

This method has the advantage that shapes of waveforms can be analyzed in an objective way. We observed that the shape of the P300 component is more stable in occipital channels, where the performance for identifying letters is higher. We additionally verified that ALS P300 signatures are stable in comparison to those of healthy subjects. Further work should be conducted over larger samples to cross-check the validity of these results.

We believe that the use of descriptors based on histogram of gradient orientation, presented in this work, also can be utilized for deriving a shape metric in the space of the P300 signals which can complement other metrics based on time-domain as those defined by Mak et al. (2012). It is important to notice that the analysis of waveform shapes is usually performed in a qualitative approach based on visual inspection (Eric W. Sellers and Emanuel Donchin, 2006).

The goal of this work is to answer the question if a P300 component could be solely determined by inspecting automatically their waveforms. We conclude affirmatively, though two very important issues still remain:

First (1), the stability of the P300 in terms of its shape is crucial: the averaging procedure, montages, the signal to noise ratio and spatial filters all of them are non-physiological factors that affect the stability of the shape of the P300 ERP. We tested a preliminary approach to assess if the morphological shape of the P300 can be stabilized by applying different shifts to segments and we verified that there is a better performance when a correct single-trial alignment is applied. We also applied Dynamic Time Warping (DTW) (Casarotto et al., 2005) but we were unable to find a substantial improvement. Further work to study the stability of the P300 signature component needs to be addressed.

The second (2) problem is the amplitude variation of the P300. We propose a solution by standardizing the signal, shown in Eq. 2. It has the effect of normalizing the peak-to-peak amplitude, moderating its variation. It has also the advantage of reducing noise that were not reduced by the averaging procedure. It is important to remark that the signal variance depends on the number of single-trials segments used to compute it (Van Drongelen, 2006). The standardizing process converts the signal to unit signal variance which makes it independent of the number k_a of signals averaged. Although this is initially an advantageous approach, the standardizing process reduces the amplitude of any significant P300 complex diminishing its automatic interpretation capability.

In our opinion, the best benefit of the presented method is that a closer collaboration with physicians can be fostered, since this procedure intent to imitate human visual observation. Automatic classification of patterns in EEG that are specifically identified by their shapes like K-Complex, Vertex Waves, Positive Occipital Sharp Transient (Hartman, 2005) are a prospect future work to be considered. We are currently working in unpublished material analyzing KComplex that could eventually provide assistance to physicians to locate these EEG patterns, specially in long recording periods, frequent in sleep research. Additionally, it can be used for artifact removal which is performed on many occasions by visually inspecting signals. This is due to the fact that the descriptors are a direct representation of the shape of signal waveforms. In line with these applications, it can be used to build a database (Chavarriaga et al., 2017) of quantitative representations of waveforms and improve atlases (Hartman, 2005), which are currently based on qualitative descriptions of signal shapes.

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

This work is part of the PhD thesis of RR which is directed by JS and codirected by AV.

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Table 1. Percentage of correctly predicted letters while performing an offline BCI Simulation for the best performing channel for each subject of the public dataset 008-2014. The spelled words are *GATTO*, *MENTE*, *VIOLA* and *REBUS*.

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%

Table 2. Percentage of correctly predicted letters while performing an offline BCI Simulation for the best performing channel for each healthy subject. The spelled words are *MANSO*,*CINCO*,*JUEGO* and *QUESO*.

Participant	BPC	Performance
1	Oz	40%
2	PO7	30%
3	P4	40%
4	P4	45%
5	P4	60%
6	Pz	50%
7	PO7	70%
8	P4	50%

Figure 1. Example of the 6×6 Speller Matrix used in the study. Rows and columns flash intermittently in random permutations.

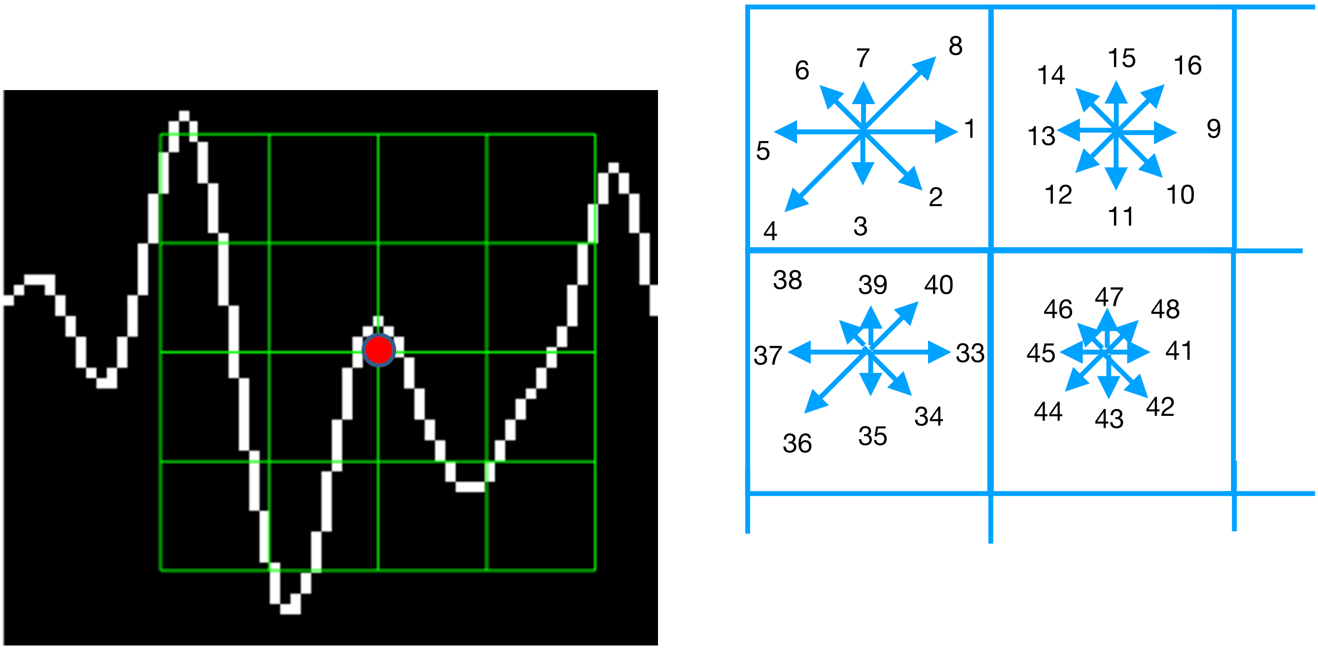

Figure 2. Example of a patch and a scheme of the orientation's histogram computation.Plot of the signal, a keypoint and the corresponding patch. Orientations on two blocks of the patch

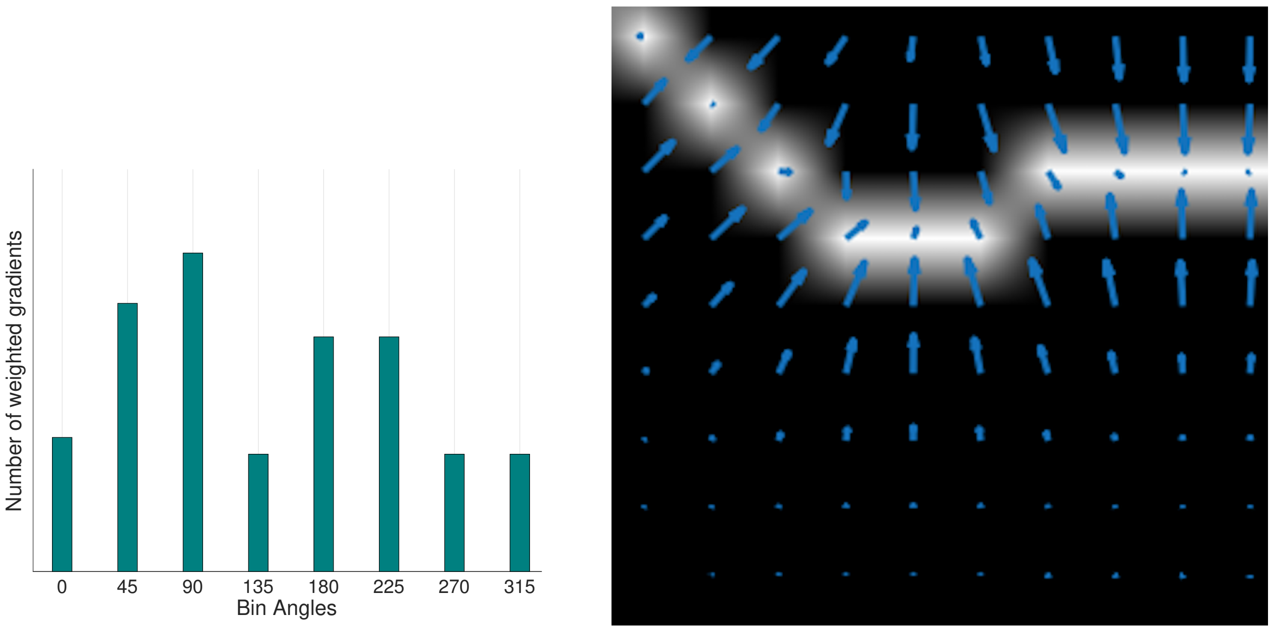

Figure 3. Example of a patch and a scheme of the orientation's histogram computation. Only the upper-left four blocks are visible. The first eight orientations of the first block, are labeled from 1 to 8 clockwise. The orientation of the second block $B_{1,2}$ is labeled from 9 to 16. This labeling continues left-to-right, up-down until the eight orientations for all the sixteen blocks are assigned. They form the corresponding kp-descriptor of 128 coordinates. The length of each arrow represent the value of the histogram on each direction for each block.

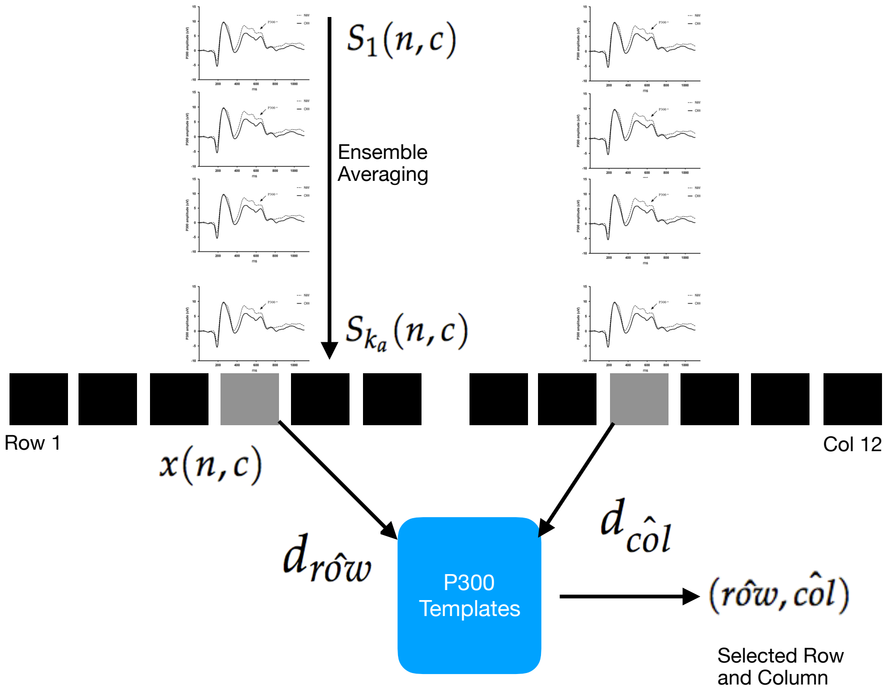

Figure 4. Single trial segments S_i are averaged for the 6 rows and 6 columns. From the averaged signal, the image of the signal plot is generated and each descriptor is computed. By comparing each descriptor against the set of templates, the P300 ERP can be detected, and finally the desired letter from the matrix can be inferred.

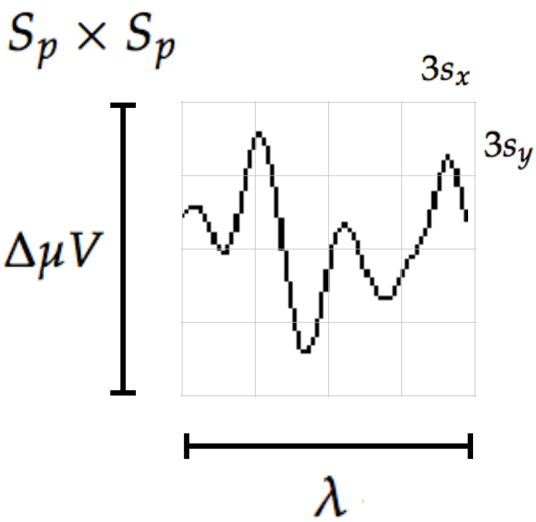

Figure 5. The scale of local patch is selected in order to capture the whole transient event. The size of the patch is $S_p \times S_p$ pixels. The vertical size consists of 4 blocks of size $3s_y$ pixels which is long enough as to contain the signal $\Delta\mu V$, the peak-to-peak amplitude of the transient event. The horizontal size includes 4 blocks of $3s_x$ and covers the entire duration in seconds of the transient signal event, λ.

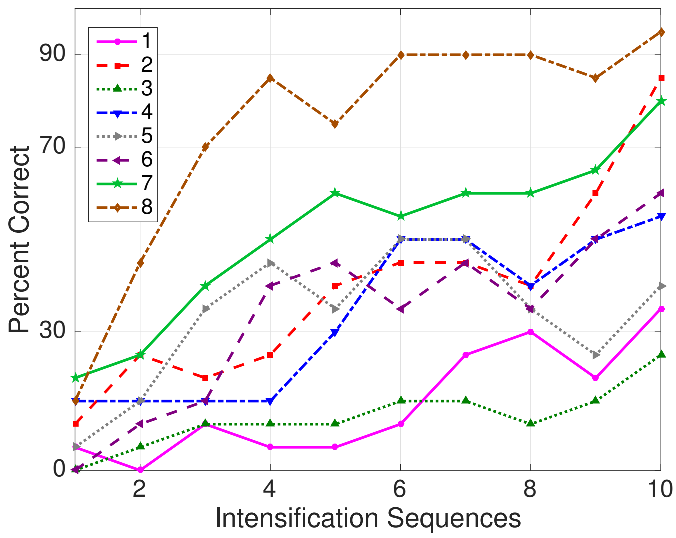

Figure 6. Performance curves for the eight subjects included in the dataset of ALS patients. Three out of eight subjects achieved the necessary performance to implement a valid P300 speller.

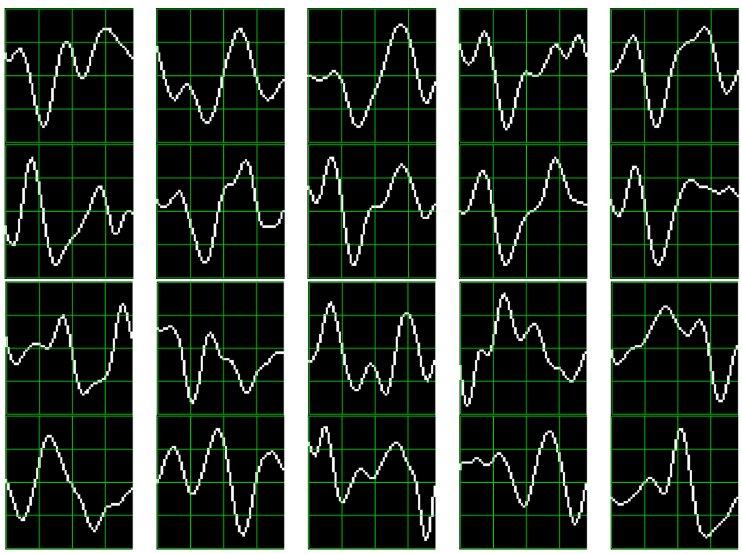

Figure 7. P300 template patches for subjects 8 and 3. As traditional done in neuroscience research, downward is positive.