

Histogram of Gradient Orientations of Signal Plots applied to P300 Detection

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2 ABSTRACT

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4 The analysis of Electroencephalographic (EEG) signals is of ulterior importance for decoding
5 patterns that could improve the implementation of Brain Computer Interfaces (BCI). These
6 systems are meant to provide alternative pathways to transmit volitional information which could
7 potentially enhance the quality of life of patients affected by neurodegenerative disorders and
8 other mental illness. Of particular interests are those which are based on the recognition of
9 Event-Related Potentials (ERP) because they can be elicited by external stimuli and used to
10 implement spellers, to control external devices or even avatars in virtual reality environments.
11 This work mimics what electroencephalographers have been doing clinically, visually inspecting
12 and categorizing phenomena within the EEG by the extraction of features from images of signal
13 plots. It also aims to provide a framework to analyze, characterize and classify EEG signals, with
14 a focus on the P300, an ERP elicited by the oddball paradigm of rare events. The validity of the
15 method is shown by offline processing a public dataset of Amyotrophic Lateral Sclerosis (ALS)
16 patients and an own dataset of healthy subjects.

17 **Keywords:** electroencephalography, histogram of gradient orientations, brain-computer interfaces, P300, SIFT, amyotrophic lateral
18 sclerosis, naive-bayes near neighbours, waveforms

1 INTRODUCTION

19 Although recent advances in neuroimaging techniques, particularly radio-nuclear and radiological
20 scanning methods (Schomer and Silva, 2010), have diminished the prospects of the traditional
21 Electroencephalography (EEG), the advent and development of digitized devices has impelled for a
22 revamping of this hundred years old technology. Their versatility, ease of use, temporal resolution, ease of
23 development and production, and its proliferation as consumer devices, are pushing EEG to become the
24 de-facto non invasive portable or ambulatory method to access and harness brain information (De Vos and
25 Debener, 2014).

26 A key contribution to this expansion has been the field of Brain Computer Interfaces (BCI) (Wolpaw and
27 E., 2012) which is the pursuit of the development of a new channel of communication particularly aimed to
28 persons affected by neurodegenerative diseases.

29 One noteworthy aspect of this novel communication channel is the ability to transmit information from
30 the Central Nervous System (CNS) to a computer device and from there use that information to control a
31 wheelchair (Carlson and del R. Millan, 2013), as input to a speller application (Guger et al., 2009), in a
32 Virtual Reality environment (Lotte et al., 2013) or as aiding tool in a rehabilitation procedure (Jure et al.,
33 2016). The holly grail of BCI is to implement a new complete and alternative pathway to restore lost
34 locomotion (Wolpaw and E., 2012).

35 EEG signals are remarkably complex and have been characterized as a multichannel non-stationary
36 stochastic process. Additionally, they have high variability between different subjects and even between
37 different moments for the same subject, requiring adaptive and co-adaptive calibration and learning
38 procedures (Clerc et al., 2016). Hence, this imposes an outstanding challenge that is necessary to overcome
39 in order to extract information from raw EEG signals.

40 BCI has gained mainstream public awareness with worldwide challenge competitions like
41 Cybathlon (Riener and Seward, 2014; Novak et al., 2018) and even been broadcasted during the inauguration
42 ceremony of the 2014 Soccer World Cup. New developments have overcome the out-of-the-lab high-bar
43 and they are starting to be used in real world environments (Guger et al., 2017; Huggins et al., 2016).
44 However, they still lack the necessary robustness, and its performance is well behind any other method of
45 human computer interaction, including any kind of detection of residual muscular movement (Clerc et al.,
46 2016).

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

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

64 This article unfolds as follows: Section 2.1 is dedicated to explain the Feature Extraction method based
65 on Histogram of Gradient Orientations of the Signal Plot: Section 2.1.1 shows the preprocessing pipeline,
66 Section 2.1.2 describes the image generation of the signal plot, Section 2.1.3 presents the feature extraction
67 procedure while Section 2.1.4 introduces the Speller Matrix Letter Identification procedure. In Section 2.2,
68 the experimental protocol is expounded. Section 3 shows the results of applying the proposed technique. In
69 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 Signal to Noise Ratio (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). This matrix is composed of 6 rows and 6 columns of numbers and letters. The subject can focus on one character of the matrix. Figure 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. Figure 2 shows a scheme of the entire process.

2.1.1 Preprocessing Pipeline

The data obtained by the capturing device is digitalized and a multichannel EEG signal is constructed.

The 6 rows and 6 columns of the Speller Matrix are intensified providing the visual stimulus. The number of a row or column is a location. A sequence of twelve randomly permuted locations l conform an intensification sequence. The whole set of twelve intensifications is repeated k_a times.

- **Signal Enhancement:** This 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:** For every complete sequence of 12 intensifications of 6 rows and 6 columns, a basic artifact elimination procedure is implemented by removing the entire sequence when any signal deviates above/below $\pm 70\mu V$.
- **Segmentation:** For each of the 12 intensifications of one intensification sequence, a segment S_i^l of a window of t_{max} seconds of the multichannel signal is extracted, starting from the stimulus onset, corresponding to each row/column intensification l and to the intensification sequence i . As intensifications are permuted in a random order, the segments are rearranged corresponding to row flickering, labeled 1-6, whereas those corresponding to column flickering are labeled 7-12. 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 basal EEG so the standard 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.

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 $1 \leq l \leq 12$ segments $S_1^l(n, c), \dots, S_{k_a}^l(n, c)$, of the EEG signal where the variables $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$ correspond to sample points and channel, respectively. The parameter C 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

$$x^l(n, c) = \frac{1}{k_a} \sum_{i=1}^{k_a} S_i^l(n, c) \quad (1)$$

for $1 \leq n \leq n_{max}$ and for the channels $1 \leq c \leq C$. This provide an averaged signal $x^l(n, c)$ for the twelve locations $1 \leq l \leq 12$.

2.1.2 Signal Plotting

Averaged signal segments are standardized and scaled for $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$ by

$$\tilde{x}^l(n, c) = \left\lfloor \gamma \frac{(x^l(n, c) - \bar{x}^l(c))}{\hat{\sigma}^l(c)} \right\rfloor \quad (2)$$

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

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

and

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

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

Consequently, for a pixel (z_1, z_2) , the image $I^{(l,c)}$ is constructed according to

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

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 with $1 \leq n \leq n_{max}$ and $1 \leq c \leq C$. The value

130 $z^l(c)$ is the image vertical position where the signal's zero value has to be situated in order to fit the entire
 131 signal within the image for each channel c:

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

132 where the minimization and maximization are carried out for n varying between $1 \leq n \leq n_{max}$, and $\lfloor \cdot \rfloor$
 133 denote the rounding to the smaller nearest integer of the number.

134 In order to complete the plot $I^{(l,c)}$ from the pixels, the Bresenham (Bresenham, 1965; Ramele et al.,
 135 2016) algorithm is used to interpolate straight lines between each pair of consecutive pixels.

136 2.1.3 Feature Extraction: Histogram of Gradient Orientations

137 For each generated image $I^{(l,c)}$, a keypoint \mathbf{p}_k is placed on a pixel (x_{p_k}, y_{p_k}) over the image plot and a
 138 window around the keypoint is considered. A local image patch of size $X_p \times X_p$ pixels is constructed by
 139 dividing the window in 16 blocks of size $3s$ each one, where s is the scale of the local patch and it is an
 140 input parameter of the algorithm. It is arranged in a 4×4 grid and the pixel \mathbf{p}_k is the patch center, thus
 141 $X_p = 12s$ pixels.

142 A local representation of the signal shape within the patch can be described by obtaining the gradient
 143 orientations on each of the 16 blocks $B_{i,j}$ with $0 \leq i, j \leq 3$ and creating a histogram of gradients. This
 144 technique is based on Lowe's SIFT (Lowe, 2004) method, and it is biomimetically inspired in how the
 145 visual cortex detects shapes by analyzing orientations (Edelman et al., 1997). In order to calculate the
 146 histogram, the interval $[0, 360]$ of possible angles is divided in 8 bins, each one of 45 degrees.

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

$$h(\theta, i, j) = 3s \sum_{\mathbf{p} \in I^{(l,c)}} w_{ang}(\angle J(\mathbf{p}) - \theta) w_{ij} \left(\frac{\mathbf{p} - \mathbf{p}_k}{3s} \right) |J(\mathbf{p})| \quad (5)$$

149 where \mathbf{p} is a pixel from the image $I^{(l,c)}$, θ is the angle bin with $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$,
 150 $|J(\mathbf{p})|$ is the norm of the gradient vector in the pixel \mathbf{p} and it is computed using finite differences and $\angle J(\mathbf{p})$
 151 is the angle of the gradient vector. The scalar $w_{ang}(\cdot)$ and vector $w_{ij}(\cdot)$ functions are linear interpolations
 152 used by Lowe (2004) and Vedaldi and Fulkerson (2010) to provide a weighting contribution to eight
 153 adjacent bins. They are calculated as

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

154 with $0 \leq i, j \leq 3$ and

$$w_{ang}(\alpha) = \sum_{r=-1}^1 w\left(\frac{8\alpha}{2\pi} + 8r\right) \quad (7)$$

155 where x_i and y_i are the spatial bin centers located in $x_i, y_j \in \{-\frac{3}{2}, -\frac{1}{2}, \frac{1}{2}, \frac{3}{2}\}$, $\mathbf{v} = (v_x, v_y)$ is a vector
 156 variable and α a scalar variable. On the other hand, r is an integer that can vary freely between $[-1, 1]$
 157 which allows the argument α to be unconstrained in terms of its values in radians. The interpolating
 158 function $w(\cdot)$ is defined as $w(z) = \max(0, |z| - 1)$.

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

162 Lastly, the fixed value of 3 is a magnification factor which corresponds to the number of pixels per each
 163 block when $s = 1$. As the patch has 16 blocks and 8 bin angles are considered, for each location l and
 164 channel c a feature called *descriptor* $\mathbf{d}^{(l,c)}$ of 128 dimension is obtained.

165 Figure 3 shows an example of a patch and a scheme of the histogram computation. In (A) a plot of the
 166 signal and the patch centered around the keypoint is shown. In (B) the possible orientations on each patch
 167 are illustrated. Only the upper-left four blocks are visible. The first eight orientations of the first block, are
 168 labeled from 1 to 8 clockwise. The orientations of the second block $B_{1,2}$ are labeled from 9 to 16. This
 169 labeling continues left-to-right, up-down until the eight orientations for all the sixteen blocks are assigned.
 170 They form the corresponding descriptor \mathbf{d} of 128 coordinates. Finally, in (C) an enlarged image plot is
 171 shown where the oriented gradient vector for each pixel can be seen.

172 2.1.4 Speller Matrix letter Identification

173 2.1.4.1 P300 ERP Extraction

174 Segments corresponding to row flickering are labeled 1-6, whereas those corresponding to column
 175 flickering are labeled 7-12. The extraction process has the following steps:

- 176 • **Step A:** First highlight rows and columns from the matrix in a random permutation order and obtain
 177 the Ensemble Average as detailed in steps 1, 2 and 3 in Section 2.1.1.
- 178 • **Step B:** Plot the signals $\tilde{x}^l(n, c)$, $1 \leq n \leq n_{max}$, $1 \leq c \leq C$, according Section 2.1.2 in order to
 179 generate the images $I^{(l,c)}$ for rows and columns $1 \leq l \leq 12$.
- 180 • **Step C:** Obtain the descriptors $\mathbf{d}^{(l,c)}$ for rows and columns from $I^{(l,c)}$ in accordance to the method
 181 described in Section 2.1.3.

182 2.1.4.2 Calibration

183 A trial, as defined by the BCI2000 platform (Schalk et al., 2004), is every attempt to select just one letter
 184 from the speller. A set of trials is used for calibration and once the calibration is complete it can be used to
 185 identify new letters from new trials.

186 During the calibration phase, two descriptors $\mathbf{d}^{(l,c)}$ are extracted for each available channel, corresponding
 187 to the locations l of a selection of one previously instructed letter from the set of calibration trials. These
 188 descriptors are the P300 templates, grouped together in a template set called T^c . The set is constructed
 189 using the steps described in Section 2.1.1 and the steps A, B and C of the P300 ERP extraction process.

190 Additionally, the best performing channel, bpc is identified based on the the channel where the best
 191 Character Recognition Rate is obtained.

192 2.1.4.3 Letter identification

193 In order to identify the selected letter, the template set T^{bpc} is used as a database. Thus, new descriptors
194 are computed and they are compared against the descriptors belonging to the calibration template set T^{bpc} .

- 195 • **Step D:** Match to the calibration template T^{bpc} by computing

$$\hat{row} = \arg \min_{l \in \{1, \dots, 6\}} \sum_{q \in N_T(\mathbf{d}^{(l,bpc)})} \left\| q - \mathbf{d}^{(l,bpc)} \right\|^2 \quad (8)$$

196 and

$$\hat{col} = \arg \min_{l \in \{7, \dots, 12\}} \sum_{q \in N_T(\mathbf{d}^{(l,bpc)})} \left\| q - \mathbf{d}^{(l,bpc)} \right\|^2 \quad (9)$$

197 where $N_T(\mathbf{d}^{(l,bpc)})$ is defined as $N_T(\mathbf{d}^{(l,bpc)}) = \{\mathbf{d} \in T^{bpc} / \mathbf{d} \text{ is the k-nearest neighbor of } \mathbf{d}^{(l,bpc)}\}$ for
198 the best performing channel. This set is obtained by sorting all the elements in T^{bpc} based on distances
199 between them and $\mathbf{d}^{(l,bpc)}$, choosing the k with smaller values, with k a parameter of the algorithm.
200 This procedure is based on the k-NBNN algorithm (Boiman et al., 2008).

201 By computing the aforementioned equations, the letter of the matrix can be determined from the intersection
202 of the row \hat{row} and column \hat{col} . Figure 2 shows a scheme of this process.

203 2.2 Experimental Protocol

204 To verify the validity of the proposed framework and method, the public dataset 008-2014 (Riccio et al.,
205 2013) published on the BNCI-Horizon website (Brunner et al., 2014) by IRCCS Fondazione Santa Lucia,
206 is used. Additionally, an own dataset with the same experimental conditions is generated. Both of them are
207 utilized to perform an offline BCI Simulation to decode the spelled words from the provided signals.

208 The algorithm is implemented using VLFeat (Vedaldi and Fulkerson, 2010) Computer Vision libraries
209 on MATLAB V2014a (Mathworks Inc., Natick, MA, USA). Furthermore, in order to enhance the impact
210 of our paper and for a sake of reproducibility, the code of the algorithm has been made available at:
211 <https://bitbucket.org/itba/hist>.

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

214 2.2.1 P300 ALS Public Dataset

215 The experimental protocol used to generate this dataset is explained in (Riccio et al., 2013) but can
216 be summarized as follows: 8 subjects with confirmed diagnoses but on different stages of ALS disease,
217 were recruited and accepted to perform the experiments. The Visual P300 detection task designed for this
218 experiment consisted of spelling 7 words of 5 letters each, using the traditional P300 Speller Matrix (Farwell
219 and Donchin, 1988). The flashing of rows and columns provide the deviant stimulus required to elicit this
220 physiological response. The first 3 words are used for calibration and the remaining 4 words, for testing
221 with visual feedback. A trial is every attempt to select a letter from the speller. It is composed of signal
222 segments corresponding to $k_a = 10$ repetitions of flashes of 6 rows and $k_a = 10$ repetitions of flashes of
223 6 columns of the matrix, yielding 120 repetitions. Flashing of a row or a column is performed for 0.125
224 s, following by a resting period (i.e. inter-stimulus interval) of the same length. After 120 repetitions an
225 inter-trial pause is included before resuming with the following letter.

226 The recorded dataset was sampled at 256 Hz and it consisted of a scalp multichannel EEG signal for
 227 electrode channels Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, identified according to the 10-20 International
 228 System, for each one of the 8 subjects. The recording device was a research-oriented digital EEG device
 229 (g.Mobilab, g.Tec, Austria) and the data acquisition and stimuli delivery were handled by the BCI2000
 230 open source software (Schalk et al., 2004).

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

235 2.2.2 P300 for healthy subjects

236 We replicate the same experiment on healthy subjects using a wireless digital EEG device (g.Nautilus,
 237 g.Tec, Austria). The experimental conditions are the same as those used for the previous dataset, as detailed
 238 in section 2.2.1. The produced dataset is available in a public online repository (Ramele et al., 2017).

239 Participants are recruited voluntarily and the experiment is conducted anonymously in accordance with
 240 the Declaration of Helsinki published by the World Health Organization. No monetary compensation
 241 is handed out and all participants agree and sign a written informed consent. This study is approved
 242 by the *Departamento de Investigación y Doctorado, Instituto Tecnológico de Buenos Aires (ITBA)*. All
 243 healthy subjects have normal or corrected-to-normal vision and no history of neurological disorders. The
 244 experiment is performed with 8 subjects, 6 males, 2 females, 6 right-handed, 2 left-handed, average age
 245 29.00 years, standard deviation 11.56 years, range 20-56 years.

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

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

253 2.2.3 Parameters

254 The patch size is $X_P = 12s \times 12s$ pixels, where s is the scale of the local patch and it is an input parameter
 255 of the algorithm. The P300 event can have a span of 400 ms and its amplitude can reach $10\mu V$ (Rao, 2013).
 256 Hence it is necessary to utilize a signal segment of size $t_{max} = 1$ second and a size patch X_P that could
 257 capture an entire transient event. With this purpose in consideration, the s value election is essential.

258 We propose the Equations 10 and 11 to compute the scale value in horizontal and vertical directions,
 259 respectively.

$$s_x = \frac{\gamma \lambda F_s}{12} \quad (10)$$

$$s_y = \frac{\gamma \Delta\mu V}{12} \quad (11)$$

260 where λ is the length in seconds covered by the patch, F_s is the sampling frequency of the EEG signal
 261 (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 determines that 1 pixel represents $\frac{1}{\gamma} = \frac{1}{4} \mu V$ on the vertical direction and $\frac{1}{F_s \gamma} = \frac{1}{64}$ seconds on the horizontal direction. The keypoints p_k are located at $(x_{p_k}, y_{p_k}) = (0.55 F_s \gamma, z^l(c)) = (35, z^l(c))$ for the corresponding channel c and location l (see Equation 4). 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).

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

3 RESULTS

Table 1 shows the results of applying the proposed algorithm to the subjects of the public dataset of ALS patients. 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 for calibration, and the remaining four are used for testing. The best performing channel bpc is informed as well. The target ratio is 1 : 36; hence chance level is 2.8%. It can be observed that the best performance of the letter identification method is reached in a dissimilar channel depending on the subject being studied. This table shows for comparison the obtained performance rates using single-channel signals with the SVM (Scholkopf and Smola, 2001) classifier. This method is configured to use a linear kernel. The best performing channel, where the best letter identification rate was achieved, is also depicted.

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. Figure 5 shows the performance curves for varying intensification sequences for the subjects included in the dataset of ALS patients. It can be noticed that the percentage of correctly identified letters depends on the number of intensification sequences that are used to obtain the averaged signal. Moreover, when the number of intensification sequences tend to 1, which corresponds to single-intensification character recognition, the performance is reduced. As mentioned before, the SNR of the P300 obtained from only one segment of the intensification sequence is very low and the shape of its P300 component is not very well defined.

In Table 2 the results obtained for 8 healthy subjects are shown. It can be observed that the performance is above chance level and higher than those achieved by the other method.

Tables 3 and 4 are presented in order to compare the performance of the Histogram of Gradient Orientations (HIST) method versus a multichannel version of the SWLDA and SVM classification algorithms for both datasets. The feature was formed by concatenating all the channels (Krusienski et al., 2006). SWLDA is the methodology proposed by the ALS dataset's publisher. Since authors Riccio et al. (2013) did not report the Character Recognition Rate obtained for this dataset, we replicate their procedure and include the performance obtained with the SWLDA algorithm at letter identification. It was verified that HIST method has an improved performance at letter identification than other methods that process the signals on a channel by channel strategy, and it even has a comparable performance against other methods like SWLDA or SVM, which uses a multichannel feature.

302 The P300 ERP consists of two overlapping components: the P3a and P3b, the former with frontocentral
303 distribution while the later stronger on centroparietal region (Polich, 2007). Hence, the standard practice is
304 to find the stronger response on the central channel Cz (Riccio et al., 2013). However, Krusienski et al.
305 (2006) show that the response may also arise in occipital regions. We found that by analyzing only the
306 waveforms, occipital channels PO8 and PO7 show higher performances for some subjects.

307 As subjects have varying *latencies* and *amplitudes* of their P300 components, they also have a varying
308 stability of the *shape* of the generated ERP (Nam et al., 2010). Figure 6 shows 10 sample P300 templates
309 patches for patients 8 and 3 from the dataset of ALS patients. It can be discerned that in coincidence with
310 the performance results, the P300 signature is more clear and consistent for subject 8 (A) while for subject
311 3 (B) the characteristic pattern is more difficult to perceive.

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

319 It is important to remark that when applied to binary images obtained from signal plots, the feature
320 extraction method described in Section 2.1.3 generates sparse descriptors. Under this subspace we found
321 that using the cosine metric yielded a significant performance improvement. On the other hand, the unary
322 classification scheme based on the NBNN algorithm proved very beneficial for the P300 Speller Matrix.
323 This is due to the fact that this approach solves the unbalance dataset problem which is inherent to the
324 oddball paradigm (Tibon and Levy, 2015).

4 DISCUSSION

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

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

331 It was verified that this method has an improved performance at letter identification than other methods
332 that process the signals on a channel by channel strategy, and it even has a comparable performance against
333 other methods like SWLDA or SVM, which uses a multichannel feature. Furthermore, this method has the
334 advantage that shapes of waveforms can be analyzed in an objective way. We observed that the shape of
335 the P300 component is more stable in occipital channels, where the performance for identifying letters
336 is higher. We additionally verified that ALS P300 signatures are stable in comparison to those of healthy
337 subjects.

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

342 inspection (Sellers et al., 2006), and a complementary methodology which offer a quantitative metric will
343 be beneficial to these routinely analysis of the waveform of ERPs.

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

347 First, the stability of the P300 in terms of its shape is crucial: the averaging procedure, montages, the
348 signal to noise ratio and spatial filters all of them are non-physiological factors that affect the stability of
349 the shape of the P300 ERP. We tested a preliminary approach to assess if the morphological shape of the
350 P300 of the averaged signal can be stabilized by applying different alignments of the stacked segments (see
351 Figure 2) and we verified that there is a better performance when a correct segment alignment is applied.
352 We applied Dynamic Time Warping (DTW) (Casarotto et al., 2005) to automate the alignment procedure
353 but we were unable to find a substantial improvement. Further work to study the stability of the P300
354 signature component needs to be addressed.

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

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

CONFLICT OF INTEREST STATEMENT

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

AUTHOR CONTRIBUTIONS

376 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. Character recognition rates for the public dataset of ALS patients using the Histogram of Gradient (HIST) calculated from single-channel plots. Performance rates using single-channel signals with the SVM classifier are shown for comparison. The best performing channel *bpc* for each method is visualized

Participant	<i>bpc</i>	HIST	<i>bpc</i>	Single Channel SVM
1	Cz	35%	Cz	15%
2	Fz	85%	PO8	25%
3	Cz	25%	Fz	5%
4	PO8	55%	Oz	5%
5	PO7	40%	P3	25%
6	PO7	60%	PO8	20%
7	PO8	80%	Fz	30%
8	PO7	95%	PO7	85%

Table 2. Character recognition rates for the own dataset of healthy subjects using the Histogram of Gradient (HIST) calculated from single-channel plots. Performance rates using single-channel signals with the SVM classifier are shown for comparison. The best performing channel *bpc* for each method is visualized.

Participant	<i>bpc</i>	HIST	<i>bpc</i>	Single Channel SVM
1	Oz	40%	Cz	10%
2	PO7	30%	Cz	5%
3	P4	40%	P3	10%
4	P4	45%	P4	35%
5	P4	60%	P3	10%
6	Pz	50%	P4	25%
7	PO7	70%	P3	30%
8	P4	50%	PO7	10%

Table 3. Character recognition rates for the public dataset of ALS patients using the Histogram of Gradient (HIST) calculated from plots of single channels with the best performing channel *bpc* informed as well. Performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Cz	35%	45%	40%
2	Fz	85%	30%	50%
3	Cz	25%	65%	55%
4	PO8	55%	40%	50%
5	PO7	40%	35%	45%
6	PO7	60%	35%	70%
7	PO8	80%	60%	35%
8	PO7	95%	90%	95%

Table 4. Character recognition rates for the own dataset of healthy subjects using the Histogram of Gradient (HIST) calculated from plots of single channels with the best performing channel *bpc* informed as well. Performance rates obtained by SWLDA and SVM classification algorithms with a multichannel concatenated feature.

Participant	<i>bpc</i> for HIST	HIST	Multichannel SWLDA	Multichannel SVM
1	Oz	40%	65%	40%
2	PO7	30%	15%	10%
3	P4	40%	50%	25%
4	P4	45%	40%	20%
5	P4	60%	30%	20%
6	Pz	50%	35%	30%
7	PO7	70%	25%	30%
8	P4	50%	35%	20%

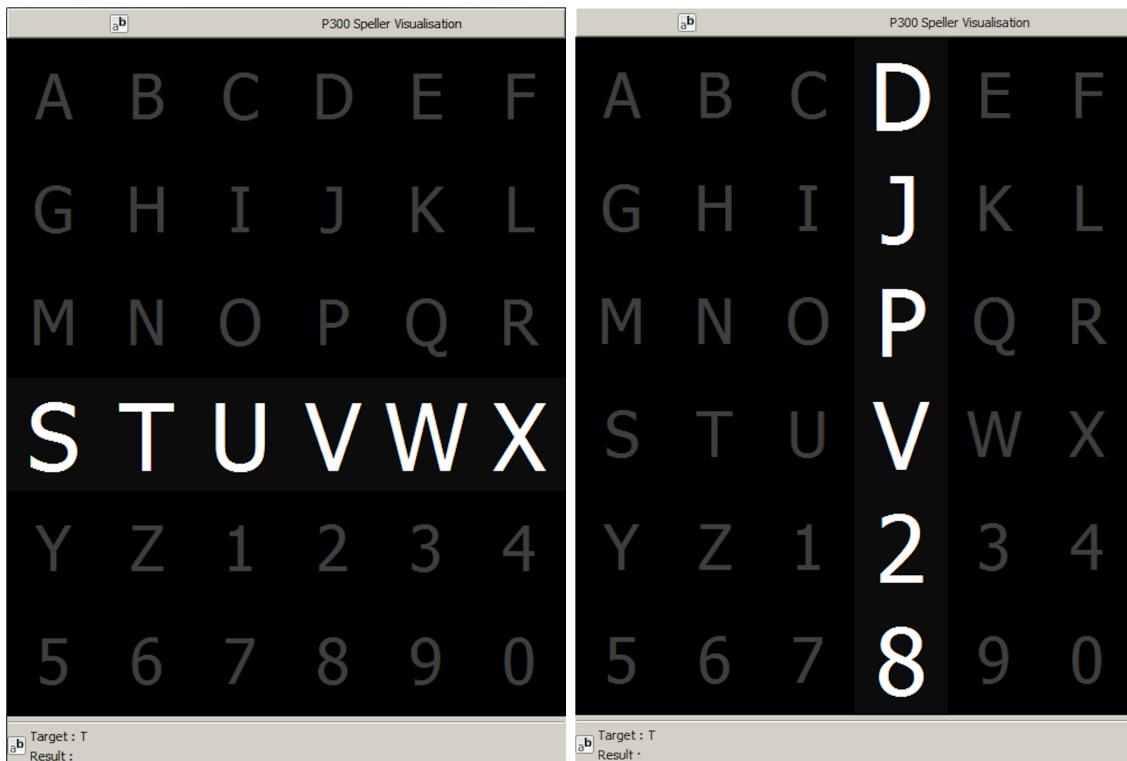


Figure 1. Example of the 6×6 Speller Matrix used in the study obtained from the OpenVibe software. Rows and columns flash in random permutations.

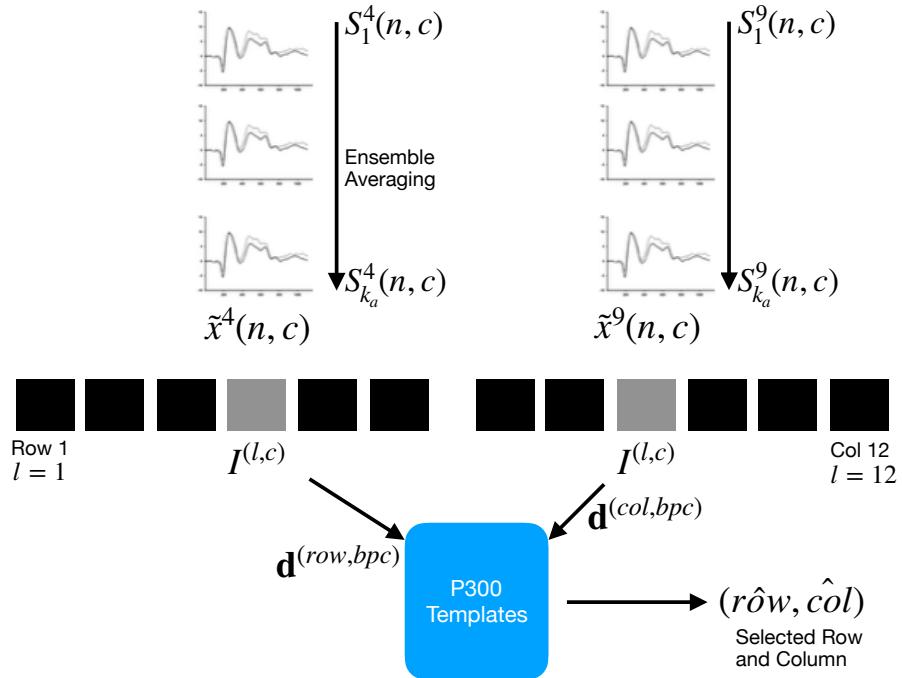


Figure 2. For each column and row, an averaged, standardized and scaled signal $\tilde{x}^l(n, c)$ is obtained from the segments S_i^l corresponding to the k_a intensification sequences with $1 \leq i \leq k_a$ and location l varying between 1 and 12. From the averaged signal, the image $I^{(l,c)}$ of 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.

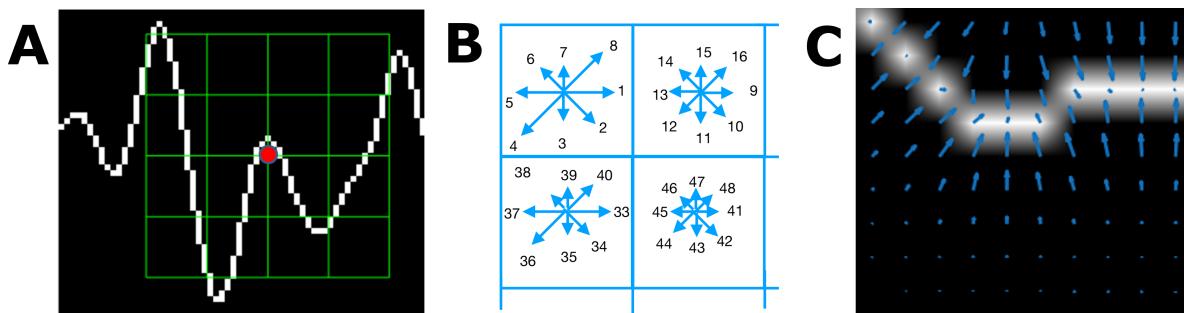


Figure 3. (A) Example of a plot of the signal, a keypoint and the corresponding patch. (B) A scheme of the orientation's histogram computation. Only the upper-left four blocks are visible. The first eight orientations of the first block, are labeled from 1 to 8 clockwise. The orientation of the second 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 descriptor of 128 coordinates. The length of each arrow represent the value of the histogram on each direction for each block. (C) Vector field of oriented gradients. Each pixel is assigned an orientation and magnitude calculated using finite differences.

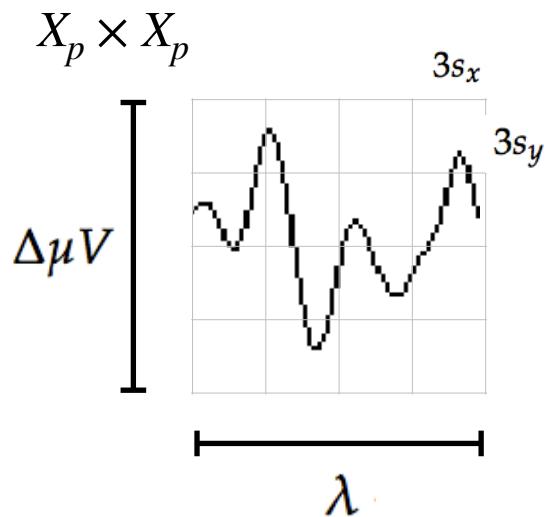


Figure 4. The scale of local patch is selected in order to capture the whole transient event. The size of the patch is $X_p \times X_p$ pixels. The vertical size consists of 4 blocks of size $3s_y$ pixels which is high enough as to contain the signal $\Delta\mu V$, the peak-to-peak amplitude of the transient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

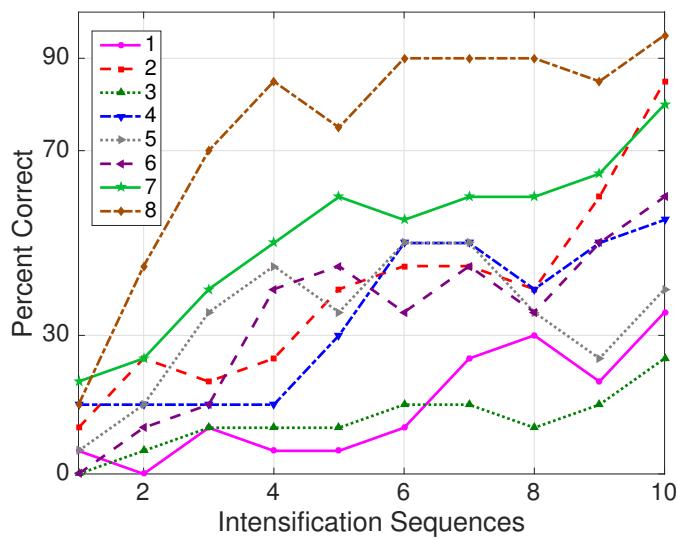


Figure 5. Performance curves for the eight subjects included in the dataset of ALS patients. Three out of eight subjects achieved the necessary performance to implement a valid P300 speller.

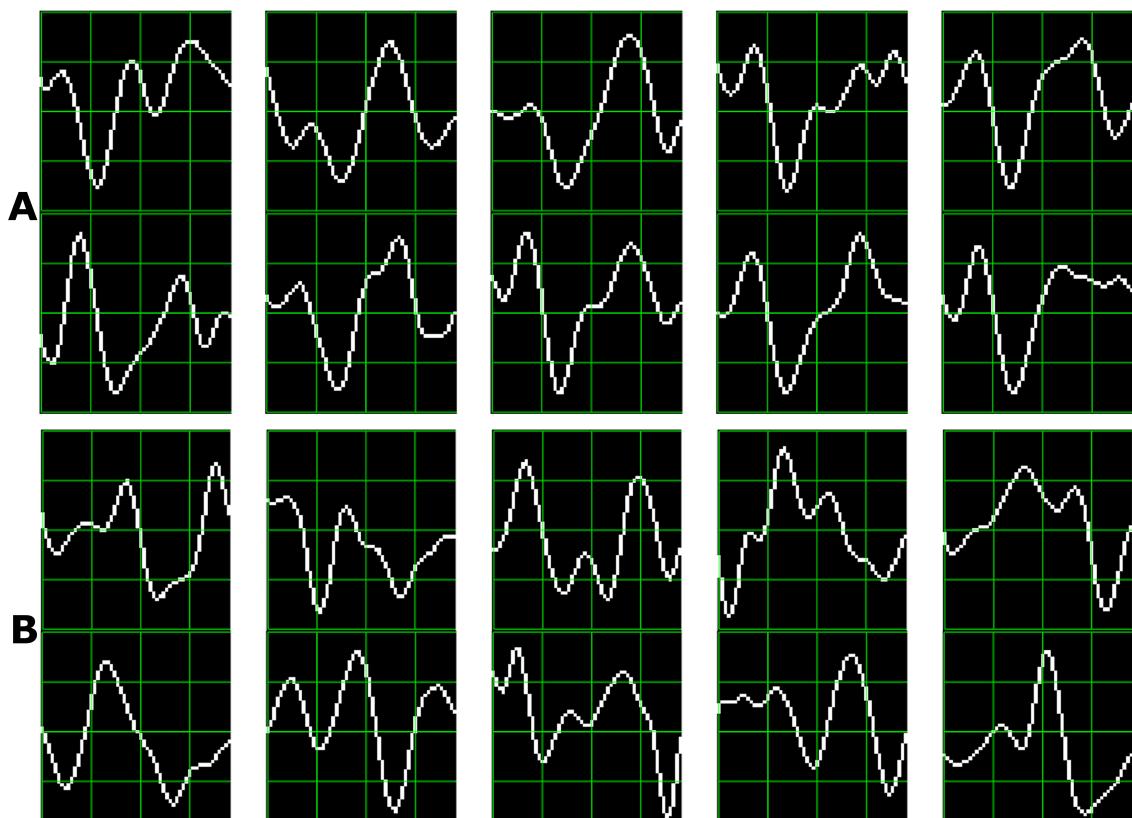


Figure 6. Ten sample P300 template patches for subjects 8 (A) and 3 (B) of the ALS Dataset. Downward deflection is positive polarity.