Article

EEG characterization and classification based on histograms of visual gradients

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1   **Abstract:** The analysis of Electroencephalograpy (EEG) signals for Amyotrophic Lateral Sclerosis
2   (ALS) patients is of ulterior importance to elucidate different patterns or markers that could be
3   potentially used to aid in diagnosis or treatment and to implement Brain Computer Interface
4   (BCI) systems which may provide alternative pathways to transmit volitional information to
5   enhance patient's quality of life. Of particular interests are those which are based on the
6   recognition of Event-Related Potentials (ERP) which are shown to be more robust to the
7   unavoidable physical impairment which comes with this motor neuron disease. This work mimics
8   what electroencephalographers has been doing clinically, visually inspecting and categorizing
9   phenomena within the EEG, and provides a framework to analyse and characterize EEG signals,
10 with a focus on the P300, an ERP elicited by the oddball paradigm of rare events. The validity of the
11 method is shown by off-line processing a public dataset of ALS patients.

12 **Keywords:** electroencephalography (EEG); BCI; P300; ALS; classification; HOG; SIFT

0. Introduction

14   Although impressive advances in neuroimagining techniques (particularly radio-nuclear
15 and radiological scanning methods) [1] has diminished the prospects of the traditional
16 Electroencephalography (EEG), the advent and development of digitalized devices has pressed for a
17 revamping of this hundredth years old technology. Their versatility, ease of use, temporal resolution,
18 ease of development and fabrication, and its proliferation as consumer devices, is pushing EEG to
19 become the de-facto non invasive method to access and harness brain information.

20   Key contribution to this development has been the field of Brain Computer Interfaces (BCI) [2]
21 which is the pursuit of the development of a new channel of communication particularly aimed to
22 persons affected by neuro-degenerative diseases.

23   One very noteworthy aspect of this communication channel is the ability to volitionally transmit
24 information from the Central Nervous System (CNS), to a computer device and from there use that
25 information to control a wheelchair [3], as input to a speller application [4], or as aiding tool in a
26 rehabilitation procedure [5]. The holly grail of BCI is to implement a new complete and alternative
27 pathway to restore lost locomotion [2].

28   EEG signals are remarkably complex and have been characterized as a multichannel
29 non-stationary stochastic process and even considered random enough as to be used as a source
30 of pseudo random number generator [6]. Additionally, they have a high variability between different
31 subjects and even between different moments for the same subject, requiring an adaptive and
32 co-adaptive calibration and learning procedures [7]. Hence, this imposes an outstanding challenge
33 that is necessary to overcome in order to extract information from raw EEG signals.

EEG markers [7] that can be used to transmit volitionally information are limited, and each one of them has a particular set or combination of appropriate methods to decode them. Inevitably, it is often necessary to implement many distinct and specialized algorithmic methods, to filter the signal, enhance its SNR, and try to determine some meaning out of it.

In this work a new method to characterize EEG signals is presented, expanded and detailed. Its validity is verified by processing off-line data for ALS patients. This is the continuation of the work previously presented in [8], where it was applied to rhythmic patterns, and that it can be extended to describe transient events like those produced by the P300[9].

The method is based on the morphological analysis of the shape of the EEG signal[10,11] and was inspired by mimicking what traditionally electroencephalographers have been performing for almost a century: visually inspecting raw signals.

In brief, this paper reports a straightforward method to, first characterize EEG signals based on the identification of their morphological shapes, and how this characterization can be used to implement a BCI scheme to identify Event Related Potentials, particularly the well-known P300, on an off-line and public dataset.

1. Materials and Methods

Besides new novel applications of BCI, the goal of the entire discipline is to provide communication assistance to people affected by neuro-degenerative diseases. It is understood that for people suffering from ALS, even though this pathology do not harm the CNS, their brain signals do suffer slow and deteriorating changes that may lead to different EEG patterns [12,13].

BCI has gained mainstream public awareness and recently even held a peculiar Olympics [13] and been broadcasted during the inauguration of the last World Cup. New developments have overcome the out-of-the-lab high-bar and they are starting to be used in real world environments[14]. 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 remaining muscular movement [7].

To verify the validity of the proposed framework and method, the public dataset 008-2014 published on the BNCI-Horizon website [15] was used to perform a binary classification task on the provided signals. The algorithm was implemented using the VLFeat [16] Computer Vision libraries on MATLAB 2014a (Mathworks Inc., Natick, MA, USA).

1.1. Experimental protocol

The protocol is explained in [15] 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 task objective was meant to spell 7 words of 5 letter each. The first 3 runs were used for training and the remaining 4 for testing with visual feedback. A trial, for this experiment, was defined as every attempt to select a letter from the speller, and it was composed of 10 repetitions of flashes of 6 rows and 6 columns of the traditional 6x6 P300 matrix , yielding 120 repetitions. Flashing of row/columns was performed for 0.125 s, following by a resting period of the same size. After 120 repetions and inter-trial pause was included before resuming with the following letter.

The gathered dataset was sampled at 256 Hz and consisted of 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. This dataset was published in the popular BNCI-Horizon 2020 website [17].

1.2. Algorithm

1.2.1. Preprocessing

The mandatory first step is to help to enhance the SNR of the P300 pattern above the level of basal EEG. The processing pipeline starts with applying a notch filter to the raw signal, a decimation

80 with a FIR filter of order 30 from the original 256 Hz to 32 Hz and finally applying a 4th degree 10 Hz
81 lowpass Butterworth filter.

82 1.2.2. Segmentation, Artefact Removal and Signal Averaging

83   The EEG matrix is processed on a channel by channel basis. For each word, each letter, a segment
84 of EEG signal is extracted that encompass 10 repetitions of 12 flashings, 6 rows and 6 columns. For
85 every 12 stimuli flashing, i.e. one complete sequence of repetitions of each row/column, a basic
86 artefact removal procedure of removing the entire segment if any signal goes above 70 μV is applied.
87   From every segment of 12 flashings, two epoch corresponding to a hit and two matching a no-hit
88 are constructed as segments of 1s length (256 sample points).
89   These segments, 20 for each class, are later point-to-point averaged for the whole 120 repetitions
90 group. This finally lead to 2 averaged signals for each of the 5 letters, for the 7 words, comprising a
91 set of 70 averaged signals[18].

92 1.2.3. Features

93   The central part of this method is the feature generation: the histogram of visual gradients. To
94 do so, the first step is the transformation of the signal into a temporary binary image.
95   The signal is first scaled and centered at zero by

$$\tilde{x}(t,c) = \lfloor \gamma \cdot (x(t,c) - \bar{x}(t,c)) \rfloor \tag{1}$$

96 where γ is the image scale, t is time and $x(t,c)$ is the EEG matrix defined for each t and for a particular
97 channel c.
98   Then the image is constructed by

$$I(z_1, z_2) = \begin{cases} 255 & z_1 = \gamma \cdot t; z_2 = \tilde{x}(t,c) + z(c) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

99 and used to derive local representations that will capture the visual shape of the signal.
100   Finally, the histogram of gradients, which is based on a technique from Computer Vision, the
101 SIFT [19] descriptor, is calculated on local image patches centered on sample points [16]. To do this,
102 the patch is divided in 16 blocks, arranged in a 4x4 grid and centered on $T = (x,y)$, a location within
103 the image. On each block, the bin consists of 45 degrees obtaining 8 aligning angles.
104   The values of the image gradients aligned with each angle bin are accumulated through

$$h(p,i,j) = 3 \cdot s \int w_{\text{ang}}(\angle J(\mathbf{x}) - \theta_p) \, w_{ij} \left(\frac{\mathbf{x} - T}{3s} \right) |J(\mathbf{x})| \, d\mathbf{x} \tag{3}$$

105 where s is the size of the local patch, $\angle J(\mathbf{x})$ is the gradient found at each of the 16 blocks of the patch
106 aligned with the angle θ_p. This gives a descriptor of 128 dimension as shown on Figure 1.
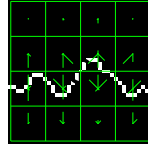
Figure 1. The local patch is located around a sample point plotted on the temporary signal. All the sample points are interpolated using the Bresenham algorithm. The 4x4 grid can be seen on the descriptor and also arrows showing the dominant gradient on each block.

1.2.4. Classification

The classification is carried out by using the discriminative semi-supervised classification method, the Naive Bayes Nearest Neighbout (NBNN) [20].

$$\hat{C} = argmin_C \sum \|d_i - NN_C(d_i)\|^2 \tag{4}$$

2. Results

In Figure 2 the grand average (point-to-point) for all the subjects is shown. The P300 characteristic curve can be seen particularly in subjects 2, and 6 and in a lesser extend in the remaining subjects. In order to obtain a valid binary classification on averaged signals, particular care was observed to avoid unbalanced samples, because that may introduce a bias in the classification procedure (signal variance is proportional to the square root of the number of samples and the procedure would be discriminating signals with different variances).Particularly in the case of the P300 response, the oddball paradigm requires that one of the stimulus need to be infrequent so that will unavoidably force that the data will be unbalanced (that is, an unequal number of trials in each condition).
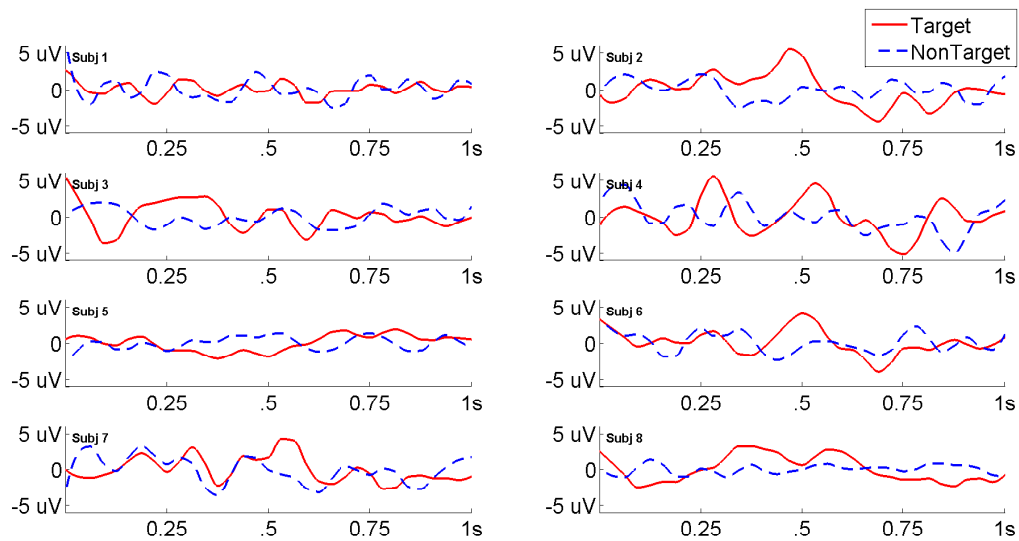
Figure 2. Point-To-Point grand averages of epochs obtained for hits (solid line) and no hits (dashed line) for each one of the 8 subjects for channel Cz. The P300 characteristic curve can be well identified on subjects 2 and 6.

Results are shown in Table 1 where BCI accuracy for the Cz channel is calculated and compared with the values obtained by the published of the dataset. Additionally the best performing channel is informed and its accuracy value. It is of particular interest that using this method, the best performing channel was not always Cz, and instead occipital channels PO8 and PO7 showed very good performance indeed [5,14].

Table 1. Results obtained for Accuracy levels by 3-fold cross validation. The values reported by the dataset publishers for Cz are reproduced here for comparison. Additionally, channel Cz BCI accuracies can be seen as well as the performance levels obtained for the BPC, the best performing channel for each subject.

Participants	Original Cz	ACC at Cz	BPC	Performance
1	0.84	0.79	Cz	0.79 ± 0.01
2	0.86	0.81	PO7	0.93 ± 0.01
3	0.87	0.78	Cz	0.78 ± 0.03
4	0.86	0.68	PO8	0.90 ± 0.01
5	0.86	0.80	PO7	0.93 ± 0.01
6	0.89	0.96	Cz	0.96 ± 0.01
7	0.89	0.78	PO7	0.93 ± 0.01
8	0.92	0.91	PO7	1.00 ± 0.00

The ITR, or BTR, in the case of reactive BCIs [2] strongly depends on the amount of signal averaging required to transmit a valid and robust selection. There is a trade-off that needs to be balanced between the required number of repetitions for each trial to guarantee robust transmission and the the achieved speed of transmission affected by the repetions. As detailed in the table 2 this method is only reduced in a 20 percent in accuracy levels even by using only one sequence of repetitions.

Table 2. Results obtained for Accuracy levels by performing a BCI simulation for the testing dataset. The BPC, best performing channel is shown and also performance levels for the 120, 60 and 12 repetitions. Finally the PR, performance reduction is described. Almost all the subjects performed around 70% even with by averaging 2 signals for each class.

Participants	BPC	ACC@120	ACC@60	ACC@12	PR
1	Cz	0.80	0.82	0.72	9%
2	PO7	0.93	0.78	0.75	18%
3	Cz	0.80	0.82	0.72	9%
4	PO8	0.93	0.78	0.65	29%
5	PO7	0.93	0.78	0.75	18%
6	Cz	0.80	0.82	0.72	9%
7	PO7	0.93	0.78	0.75	18%
8	PO7	0.93	0.78	0.75	18%

3. Conclusion

A method to characterize and classify EEG signals where the main characteristic can be both, rhythmic in nature as in motor imagery, and also transient in time space, like the P300 has been presented.

Although single trial classification was not perfectly achieved, it has been shown that this method could be applied with a P300 Speller Matrix application with increased ITR.

The adaptive behaviour of the algorithm make is well suited when the shape of the pattern elicited by the P300 response, does not conform to the predicted structure. This is because, the descriptors are directly based on how the signals actually looked like for the training and calibration step, and they do not require any prior knowledge about the signal. This is of particular relevance for studies on outliers populations as may be the case for people who suffered some neuro-degenerative disease like Lou Gehrig's disease.

The expanding of the understanding of this tool in order to automatically classify patterns in EEG, that are specifically identified by their shapes, is a prospect future work to be considered. It may also provide assistance to physician or electroencephalographers to help them locate these EEG patterns particularly in long recording periods [21], frequent in sleep research.

Moreover, this method can be used as an alternate *BCI predictor* [7] or as a tool for artefact removal (which is performed on many occasions by visually inspecting the signal).

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Conflicts of Interest: The authors declare no conflict of interest.

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 stimuli
ITR: Information Transfer Rate

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