Article

EEG Waveform Analysis with applications to Brain Computer Interfaces

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Abstract: The Electroencephalography (EEG) is not just a mere clinical tool anymore. It has become the de-facto mobile, portable, non-invasive brain imaging sensor to harness brain information in real time and translating or decoding brain signals that can be used to diagnose disease or implement Human Computer Interaction devices. The automatic processing approach which is based on using quantitative algorithms to detect the cloaked information buried in the signal, outshines the research done by the clinical EEG community which was based intensively on EEG waveforms and the structure of signal plots. Hence, the purpose of this work is to help to start to fill this gap by doing a review and description of the procedures that have been used to detect patterns in the waveforms, and to perform a benchmarking analysis of them.

Keywords: electroencephalography (EEG); ERP,BCI,waveform, signal structure

0. Introduction

Current society is demanding technology to provide the means to realize the utopia of social inclusion for people with disabilities[1]. Additionally, as societies are aging [2] the incidence of neuromuscular atrophies, strokes and other invalidating diseases is increasing. Concurrently, the digital revolution and the pervasiveness of digital gadgets have modified the way people interact with the environment through these devices [3]. All this communication is based on muscular movement [4], but these trends are pushing this boundary beyond the confines of the body and beyond the limitation of human movement. A new form of Human Machine communication which directly connects the Central Nervous System (CNS) to a machine or computer device is currently being developed: Brain Machine Interfaces (BMI), Brain Computer Interfaces (BCI) or Brain-Neural Computer Interfaces (BNCI).

At the center of all this hype, we can find a hundredth year old technology, rock-solid as a diagnosis tool, which greatly benefited from the shrinkage of sensors, the increase in computer power and the widespread development of wireless protocols and advanced electronics: the Electroencephalogram (EEG) [5].

EEG sensors are wearable [6] non-invasive, portable and mobile [7], with excellent temporal resolution, and acceptable spatial resolution [8]. This humble diagnosis device is been transformed into currently the best approach to detect, out-of-the lab in an ambulatory context, information from the Central Nervous System and to use that information to volitionally drive cars, steer drones, write emails, or control wheelchairs [9].

The clinical and historical tactic to analyze EEG signals were based on detecting visual patterns out of the EEG trace or polygraph[8]: multichannel signals were extracted and continuously plotted over a piece of paper. Electroencephalographers or Electroencephalography technician have decoded and detected patterns along the signals by visually inspecting them [5]. Nowadays clinical EEG still remains a visually interpreted test [8].

In contrast, automatic processing, or quantitative EEG, was based first on analog electronic devices and later on computerized digital processing methods [10]. They implemented mathematically and algorithmically complex procedures to decode the information with good results [9]. The best materialization of the automatic processing of EEG signals rests in the BCI discipline, where around 71.2% is based on noninvasive EEG [4].

Hence, the traditional and knowledgeable approach was mainly overshadow particularly in BCI Research, and the waveform of the EEG was replaced by pragmatically sound procedures that were difficult to link to existing clinical EEG knowledge. We aim to help fix this gap by providing a review of the methods which emphasize the waveform, the shape of the EEG signal and that can help to decode them in a supervised and semi-automated way.

The aim of this study is twofold: first to review current literature of EEG processing techniques which are based on analysis of the waveform. The second is to evaluate and study these methods by analyzing its classification performance against a pseudo-real dataset. We believe that the importance of waveform analysis methods, as described here, is that by using this methodology, collaboration could be fostered because there is a clear description and characterization of the signal, where the extensive literature which explores clinical EEG can be reviewed from the same shared perspective [11,12].

This article unfolds as follows: Section 1 will provide a brief introduction to EEG characterization and the particularities of the EEG waveform characterization. Section 3 will explain the algorithms based on the waveform that will be used to perform the benchmark. Section 4 the experimentation procedure will be explained. Results will be presented in Section 5 and finally Discussion and Conclusions will be established in the final sections.

1. Electroencephalography

The Electroencephalography consists on the measurement of small variations of electrical currents over the scalp. It is one of the most widespread used method to capture brain signals and was initially developed by Hans Berger in 1924 and has been extensively used for decades to diagnose neural diseases and other medical conditions.

The first characterization that Dr. Berger detected was the Visual Cortical Alpha Wave, the *Berger Rythm* [10]. He understood that the amplitude and shape of this rhythm was coherently associated to a cognitive action (eyes closing). We should ask ourselves if the research advancement that came after that discovery would have happened if it weren't so evident that the shape alteration was due to a very simple and verifiable cognitive process.

The EEG signal is a highly complex multi-channel time-series. It can be modeled as a linear stochastic process with great similarities to noise [13]. It is measured in microvolts, and those slightly variations are contaminated with heavy endogenous artifacts and exogenous spurious signals.

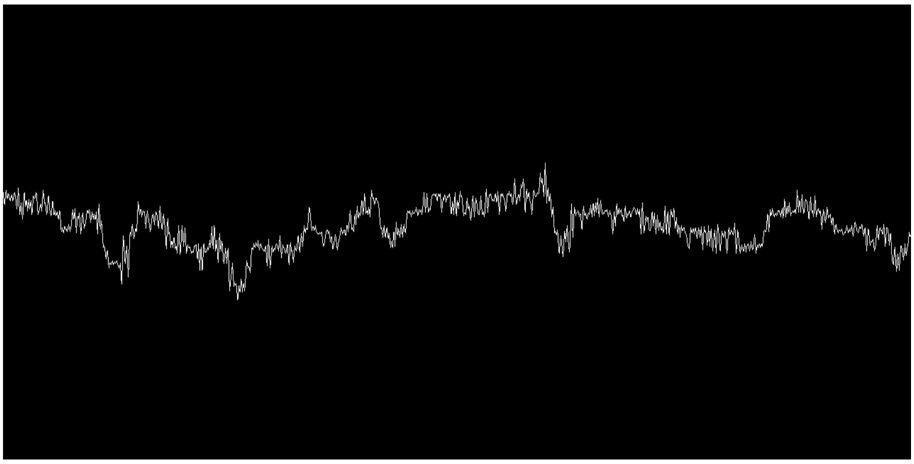

Figure 1. Sample EEG signal captured and plotted on a 2D image using the popular and commercial EPOC Emotiv using EEGLAB.

The device that captures these small variations in current potentials over the scalp is called the Electroencephalograph. Electrodes are located in predetermined positions over the head, usually embedded in saline solutions to facilitate the electrophysiological interface and are connected to a differential amplifier with a high gain which allowed the measurement of tiny signals. Although initially analog devices were developed and used, nowadays digital versions connected directly to a computer are pervasive. A detailed explanation on the particularities and modeling of EEG can be obtained from [14], and a description of its electrophysiological aspects from [15].

Overall, EEG signals can be described by their phase, amplitude, frequency and *waveform*. The following components regularly characterize EEG signals:

- Artifacts: These are signal sources which are not generated from the CNS, but can be detected from the EEG signal. These are called endogeneous or physiological when they are generated from a biological source like muscles, ocular movements, etc., and exogeneous or non-physiological when they have an external electromagnetic source like line induced currents or electromagnetic noise[16].
- Non-Stationarity: the statistical parameters that describe the EEG as a random process are not conserved through time, i.e. its mean and variance, and any other higher-order moments are not time-invariant [10].
- DC drift and trending: in EEG jargon, which is derived from concepts of electrical amplifiers theory, Direct Current (DC) refers to very low frequency components of the EEG signal which varies around a common center, usually the zero value. DC drift means that this center value drifts in time. Although sometimes considered as a nuisance that needs to get rid of, it is known that very important cognitive phenomena like Slow Cortical Potentials or Slow Activity Transients in innates do affect the drift and can be used to understand some particular brain functioning [5].
- Basal EEG activity: the EEG is the compound summation of myriads of electrical sources from the CNS. These sources generate a baseline EEG which shows continuous activity with a small or null relation with any concurrent cognitive activity or task.
- Inter-subject and intra-subject variability: EEG can be affected by the person's behavior like sleep hygiene, caffeine intake, smoking habit or alcohol intake previously to the signal measuring procedure [17].

Regarding how the EEG activity can be related to an external stimulus that is affecting the subject, it can be considered as

- Spontaneous: generally treated as noise or basal EEG.

- Evoked: activity that is time-locked to an incoming stimulus or an executed motor action. In contrast it is often called Induced activity

Additionally, according to the existence of a repeated rhythm, the EEG activity can be understood as

- Rhythmic: EEG activity consisting in waves of approximately constant frequency. It is often abbreviated RA (regular rythmic activity).
- Arrhythmic: EEG activity in which no stable rhythms are present.
- Dysrhythmic: Rhythms and/or patterns of EEG activity that characteristically appear in patient groups or rarely or seen in healthy subjects.

The number of electrodes and their positions over the scalp determines a **Spatial Structure**: signal elements can be generalized, focal or lateralized, depending on in which channel (i.e. electrode) they are found.

1.1. EEG Waveform Characterization

The shape of the signal, the waveform, can be defined as the graphed line that represents the signal's amplitude plotted against time. It can also be called EEG biomarker, EEG pattern, signal shape, signal form and a morphological signal [10].

The signal context is crucial for waveform characterization, both in a spatial and in a temporal domain [10]. Depending on the context, some specific waveform can be considered as noise while in other cases is precisely the element which has a cognitive functional implication.

A waveform can have a characteristic shape, a rising or falling phase, a pronounced plateau or it may be composed of ripples and wiggles. In order to describe them, they are characterized by its amplitude, the arch, whether they have (non)sinusoidal shape, by the presence of an oscillation or imitating a sawtooth (e.g. Motor Cortical Beta Oscillations). The characterization by their sharpness is also common, particularly in Epilepsy, and they can also be identified by their resemblance to spikes (e.g. Spike-wave discharge).

Other depictions may include, subjective definitions of sharper, arch comb or wicket shape, rectangular, containing a decay phase or voltage rise, peaks and troughs, short term voltage change around each extrema in the raw trace. Derived ratios and indexes can be used as well like peak and trough sharpness ratio, symmetry between rise and decay phase and slope ratio (steepness of the rise period to that of the adjacent decay period). For instance, wording like "Central trough is sharper and more negative that the adjacent troughs" are common in the literature.

Other regular characterizations which are based on shape features may include:

- Attenuation: Also called suppression or depression. Reduction of amplitude of EEG activity resulting from decreased voltage. When activity is attenuated by stimulation, it is said to have been "blocked" or to show "blocking".
- Hypersynchrony. Seen as an increase in voltage and regularity of rhythmic activity, or within the alpha, beta, or theta range. The term implies an increase in the number of neural elements contributing to the rhythm.
- Paroxysmal. Activity that emerges from background with a rapid onset, reaching (usually) quite high voltage and ending with an abrupt return to lower voltage activity. Though the term does not directly imply abnormality, much abnormal activity is paroxysmal.

- Monomorphic: Distinct EEG activity appearing to be composed of one dominant activity
- Polymorphic: distinct EEG activity composed of multiple frequencies that combine to form a complex waveform.
- Transient. An isolated wave or pattern that is distinctly different from background activity.

The traditional clinical approach consisted in analyzing the paper strip that was generated by the plot of the signal obtained from the device. Expert technician and physicians analyzed visually the plots looking for specific patterns that may give a hint of the underlying cognitive process or pathology. Atlases and guidelines were created in order to help in the recognition of these complex patterns. Even Video-electroencephalography scalp recordings are routinely used as a diagnostic tools [18] . The clinical EEG research has also focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG *graphoelements* [5].

Sleep Research has been studied in this way by performing Polysomnographic recordings (PSG) [19], where the different sleep stages are evaluated by visually marking waveforms or graphoelements in long-running electroencephalographic recordings, looking for patterns based on standardized guidelines. Visual characterization includes the identification or classification of certain waveform components, or transient events, based on a subjective characterization (e.g. positive or negative peak polarity) or the location within the strip. It is regular to establish an amplitude difference between different waveforms from which a relation between them is established and a structured index are created (e.g. sleep K-Complex is well characterized based on rates between positive vs negative amplitude) (REFERENCE). Other relevant EEG patterns for sleep stage scoring are alpha, theta, and delta waves, sleep spindles, polysplindles, K-complexes, vertex sharp waves (VSW), and sawtooth waves (REM Sleep).

Moreover, EEG data acquisition is a key procedure during the assessment of patients with focal Epilepsy for potential seizure surgery, where the source of the seizure activity must be reliably identified. The onset of the Epileptic Seizure is defined as the first electrical change seen in the EEG rhythm which can be visually identified from the context and it is verified against any clinical sign indicating seizure onset. The interictal epileptiform discharges (IEDs) are visually identified from the paper strip, and they are also named according to their shape: spike, spike and wave or sharp-wave discharges[20].

2. Materials and Methods

The following criteria is proposed to identify methods which are based on the signal's waveform:

1. The analysis take account the shape of the plot of the signal.
2. The pattern can be identified and verified by visual inspection.
3. The pattern matching is performed in time-domain.
4. The method encompass a feature extraction procedure.
5. The feature extraction procedure allows to create a template dictionary.
6. A single-channel processing scheme.

As described in (Mixed Domain Signal Analysis) the Pattern Matching problem in Signal processing is finding a signal given the region that best describes the structure of the pattern. All these algorithm were implemented on MATLAB 2014a (Mathworks Inc., Natick, MA, USA).

2.1. EEG Waveform Analysis Algorithms

Shape or waveform analysis methods are considered as nonparametric (in opposition to statistical or dynamical models). They explore signal's time-domain metrics or even derive more complex indexes from it [21].

One of the earliest approach to automatically process EEG data is the Peak Picking method. Although of limited usability, peak picking has been used to determine latency of transient events in EEG [22,23]. Straightforward in its implementation, it consists in selecting a component, a simple component based on the expected location of its more prominent deflection [24]. Of regular use in ERP Research, the name of many of the EEG features reference directly a peak within the component, e.g. P300 or P3a P3b or N100. This leads to a natural way to classify them visually by selecting appropriate peaks and matching their positions and amplitudes in an orderly manner. The letter provides the polarity (Positive or Negative) and the numbering shows the time referencing the stimulus onset, or the ordinal position of each peak (first, second, etc).

A related method is used in [25] where the area under the curve of the EEG is sumarized to derive a feature. This was even used in the seminal work of Farwell and Donchin on P300 [26,27]. Additionally, a logarithmic graph of the peak-to-peak amplitude which is called amplitude integrated EEG (aEEG) [28] is used nowadays in Neonatal Intensive Care Units.

Other works on EEG explored the idea to extend human capacities analyzing EEG waveforms [29] where a feature from the amplitude and frequency of its signal and its derivative in time-domain is used. Moreover, other works explored the use of Mathematical Morphology [30], where the time-domain structure of contractions and dilations were studied, and finally the seminal proposals of Fujimori, Uchida and the PAA algorithm as few of the earliest proposals where the idea of capturing the shape of the signal were established.

According to the defined criteria, the algorithms that will be evaluated are as follows:

- Matching Pursuit
- Permutation Entropy
- Slope Horizontal Chain Code
- Histogram of Gradient Orientations
- Merging of Increasing and Decreasing Sequences
- Local Binary Patterns (1-D LNBP, 1D-LBP and LBP)

All these methods provide a feature that can be used as a template, whereas all of them are based on metrics that can be extracted from the shape of the signal. These features can be used to create dictionaries or templates databases. These templates provide the basis for the pattern matching algorithm and offline classification.

2.2. Matching Pursuit - MP 1 and MP 2

Pursuit algorithms refer, in their many variants, as blind source separation(REF) techniques that assume that the EEG signal is a linear combination of different sources that comes from template's dictionaries. The underlying idea is to find the best template out of a dictionary that matches against the signal. The algorithm works iteratively, starting from the raw signal and then, the template is substracted from the signal in Graham-Schmidt approach and the process iterates. (ref Cohen book, Sanei book, Mallat and Zhang 1993).

On the other hand, Morphological Component Analysis is a variant form of Blind Source Separation which can be considered the extension of Matching Pursuit algorithm. (cita a esa parte del paper).

2.3. Permutation Entropy - PE

Bond and Pompe Permutation Entropy has been extensively used in EEG processing, particularly for Epilepsy pre-ictal detection. This method generates a code based on the orderly arrangement of sequential samples, and then derives a metric which is based on the amount of entropy of each code within the signal. For instance, a pure random signal, will achieve the maximum entropy value due to the probability of each code being equal for all of them. This method is the best representative of Waveform Complexity: Lempel-Ziv method L-Z complexity are other variants which use a different definition (Permutation Entropy a new feature for brain computer interfaces).

2.4. Slope Horizontal Chain Code - SHCC

This method is an extension of Slope Chain Code (SCC) (ref a SCC paper y a SHCC paper), and a code of a sequence of sample points is generated based on the angle between the horizontal segment and any segment, one by one. This method can be encompass as a syntactic analysis technique, where the EEG segment is represented as a series of elementary patterns, similar to tokens, due to the quantization of angles.

2.5. Histogram of Gradients Orientations - HGO

This Histogram of Gradient Orientations is based on using Computer Vision techniques to extract directly information from a signal based on the plot of a signal on a 2D image. This mimicks exactly what a person is doing by visually inspecting the plot, and the waveform. To do that, the region of the image where the signal is located is divided in a $4x4$ block and the signal bidimensional gradients is calculated. For each block within the patch, a histogram of gradient orientations, 8 circular orientations, is calculated. This histogram is concatenated for all the 16 blocks and a feature is thus formed. The details of the method can be found here [31]. This method was implemented using the VLFeat [32] Computer Vision libraries.

2.6. Experimental Protocol

Farwell and Donchin P300 Speller [26] is one the most used BCI paradigms to implement a thought translation device and to send commands to a computer in the form of selected letters, similar to typing in a virtual keyboard. This procedure exploits a cognitive phenomena called oddball paradigm: along the EEG trace of a person which is focusing on a sequence of two different visual flashing stimulus, a particular and distinctive transient component is found each time the expected stimulus flashes. This is cleverly utilized in the P300 Speller, where rows and columns of a 6x6 matrix flashes randomly but only the flashing of a column or row where the letter that a user is focusing will trigger concurrently the P300 ERP along the EEG trace.

Higher accuracy algorithms can detect it in a good-enough single-trial approach [P300 Summary], but in general these algorithms are not related to the shape of the P300 ERP. Hence it is difficult to establish a backward mapping back to a certain visual pattern within the waveform.

In order to verify each algorithm in a controlled procedure, a real ERP template is superimposed into a real EEG stream. This trace was experimentally obtained by a subject which was observing the flashing of the stimulus matrix during a P300 Speller procedure but did not engage in focusing on anyone in particular. Everything is there, except the P300 ERP component. By implementing this pseudo-real approach, it is possible to effectively control null-signals and the shape of this evoked potential following the same approach of other similar works [22,24,33].

The experiments are as follows:

- Pseudo-real dataset Classification Performance: the letter classification performance of each one of these methods.
- Latency Noise: Gaussian noise is added to the latency where the ERP template is injected into the EEG stream.
- Component Amplitude Noise: the different components of the ERP template are altered to make them less distinguishable.

Finally results for the same methods while offline processing a public dataset of real P300 patterns are also shown.

2.6.1. Pseudo-Real Dataset Generation

The template ERP is extracted from the Subject 8 of the public dataset 008-2014 [34] published on the BNCI-Horizon website [35] by IRCCS Fondazione Santa Lucia. Segments from the EEG signal are labeled as hit and are extracted for the trial number 2, and they are point-to-point coherently averaged. This P300 ERP can be seen in Fig. 2.

An EEG stream with null-P300 signal everywhere is obtained by the following procedure: The participant is 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 he/she agree and sign a written informed consent. This study is approved by the *Departamento de Investigación y Doctorado, Instituto Tecnológico de Buenos Aires (ITBA)*. The participant is healthy and have normal or corrected-to-normal vision and no history of neurological disorders. This voluntary is of unspecified gender, aged between 20-30 years old. EEG data is collected in a single recording session. She/He is seated in a comfortable chair, with her/his vision aligned to a computer screen located one meter in front of him. The handling and processing of the data and stimuli is conducted by the OpenVibe platform [36]. Gel-based active electrodes (g.LADYbird, g.Tec, Austria) are used on locations Fz, Cz, Pz, Oz, P3,P4, PO7 and PO8 according to the 10-20 international system. Reference is set to the right ear lobe and ground is preset as the AFz position. Sampling frequency is set to 250 Hz, which is the closest possible to the one used with the other dataset.

The participant is instructed to passively watch the flashing screen while not focusing on any particular letter. A questionnaire is handed out at the end of the experiment with questions about how the participant felt during it, without giving more details.

Fig. 4 shows the result of superimposing the template signal into EEG stream, time-locked to the stimulus onset. These 12 point-to-point averaged segments correspond to the first trial of the EEG stream.

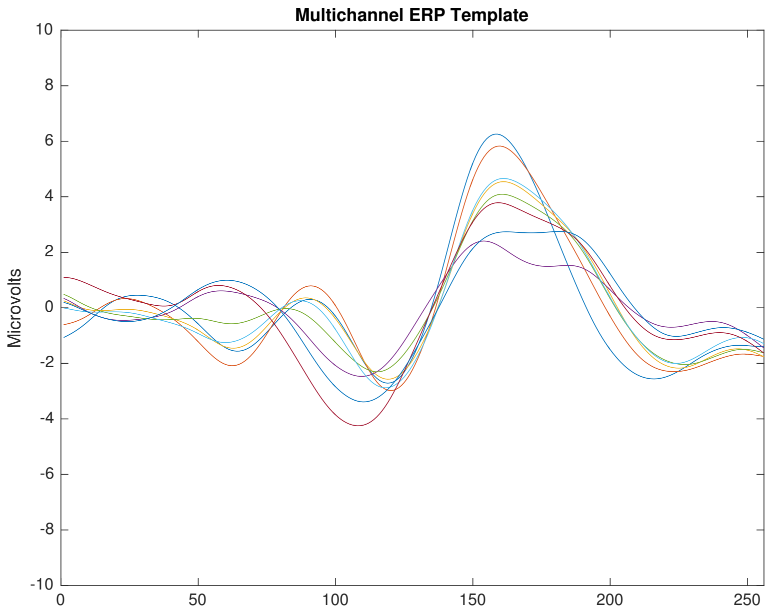

Figure 2. ERP Template obtained from the coherent point-to-point ensemble average of subject eight obtained from the BNCI Horizon public dataset. The P1, N1 and P300 peaks can be seen.

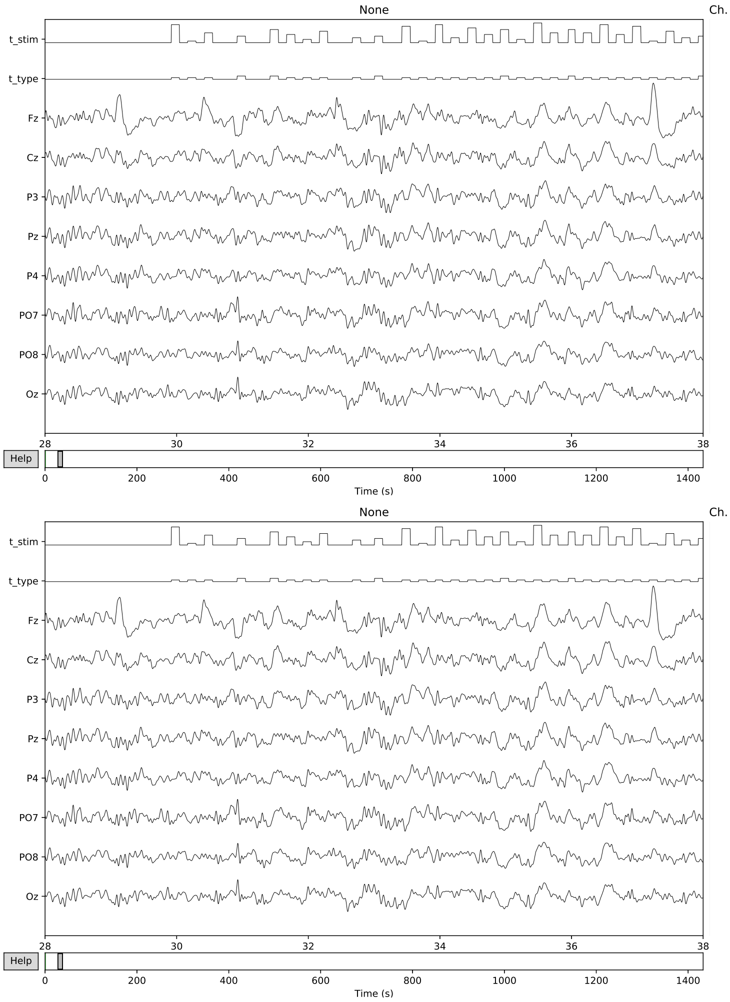

Figure 3. 8-Channel EEG signal superimposed with the ERP Template. Left show the signal with single gain and right the same signal with double gain.

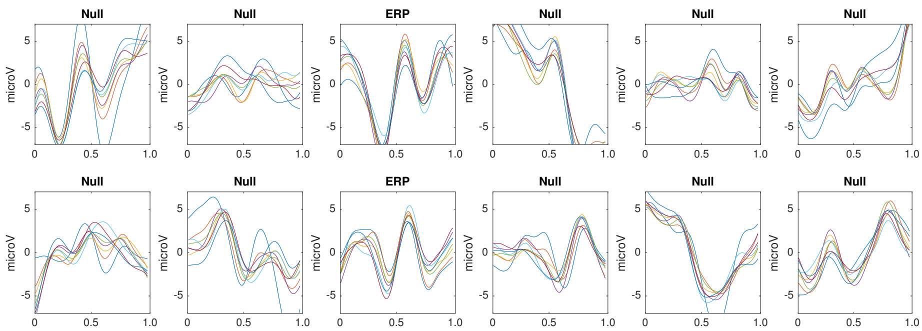

Figure 4. These are the point-to-point averaged signals for the first trial. The ERP was injected on class 3 and 9.

2.6.2. Classification

To analyze how each method identifies the hidden P300 signal, the same classification algorithm is used. The original dataset is composed of 35 trials to decode 7 words of 5 letters of the P300 matrix. Each trial is composed of 10 intensification sequences of the 6 columns and 6 rows [34]. The averaging procedure aims to extract the superimposed ERP Template and cancel out everything else on each segment.

This classification procedure identifies the row and column, matching to the template T by computing

$$\hat{row} = \arg \min_{u \in \{1,...,6\}} \sum_{q \in NN_T(f_u^{row})} \|q - f_u^{row}\|^2 \tag{1}$$

and

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

where $NN_T(f_u^l)$, $l \in \{row, col\}$ is the set of the k nearest neighbors to f_u^l and q is a template feature that belongs to it. This set is obtained by sorting all the elements in the dictionary T based on the distances between them and f_u^l, choosing the k smaller elements. This procedure is a modification of the k-NBNN algorithm [37].

By computing the aforementioned equations, the letter of the matrix can be determined from the intersection of the row $\hat{row}$ and column $\hat{col}$.

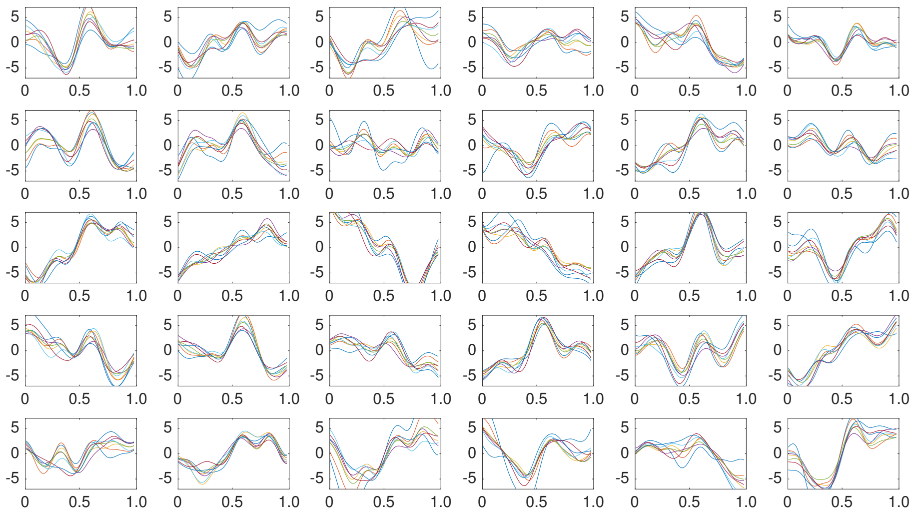

Figure 5. Coherently averaged signals containing the superimposed ERP. Each one is extracted from the 15 first trials (2 signals from each trial, one belonging to the column and the other to the row). These are the templates that are used by the classification algorithm described in 2.6.2.

3. Results

Results are shown in Table 1 and in Figure 1,2 and 3. Table 1 shows the performance to identify each letter of the standard P300 Speller Matrix, and the channel where the best performance was obtained. Figure 6 shows the performance curves for eight algorithms. Each one represents the percentage of letters that were actually predicted by the combination of feature plus a classification method. The data were divided in two, and the first 15 letters were used to derive the dictionary of templates T while the remaining 20 letters were used to measure the classification accuracy. Figure 7 shows the same results obtained when a random uniform latency shift was added to each trial. Finally, Figure 8 represents the performance values obtained when the amplitude of the N1 and P3 component of the template are randomly reduced (uniform distribution).

Table 1. Classification performance obtained for all the waveform-based algorithms. All the methods process the signal on a channel-by-channel basis, so the best performing channel is also shown. It can be understood as the channel that adds less noise to the ERP template. All the methods used 10 intensification sequences to coherently average the trials to obtain the averaged signal that was used to obtain the feature that was finally classified.

Method	Channel	Single Trial Performance
MP 1	PO8	25%
MP 2	PO7	10%
HGO	PO8	25%
PE	Cz	20%
SHCC	P4	10%
RS	Fz	15%
RS m-c		15%

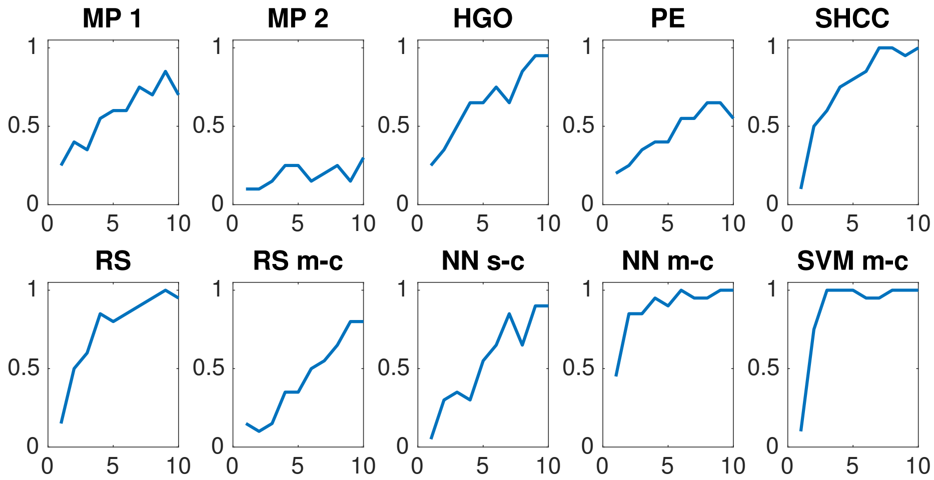

Figure 6. Performance obtained from the different methods.

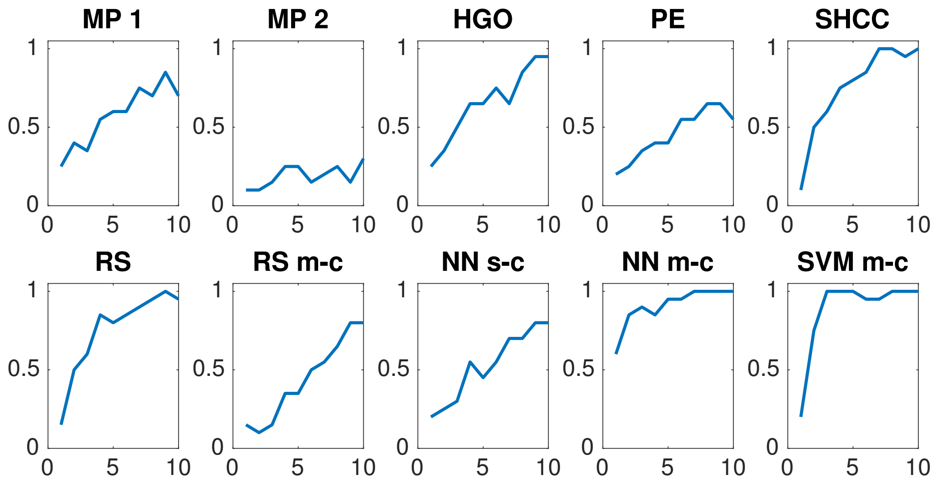

Figure 7. Performance obtained for all the methods. Latencies were artificially added to each single-trial segment. Performance is significantly reduced for all methods.

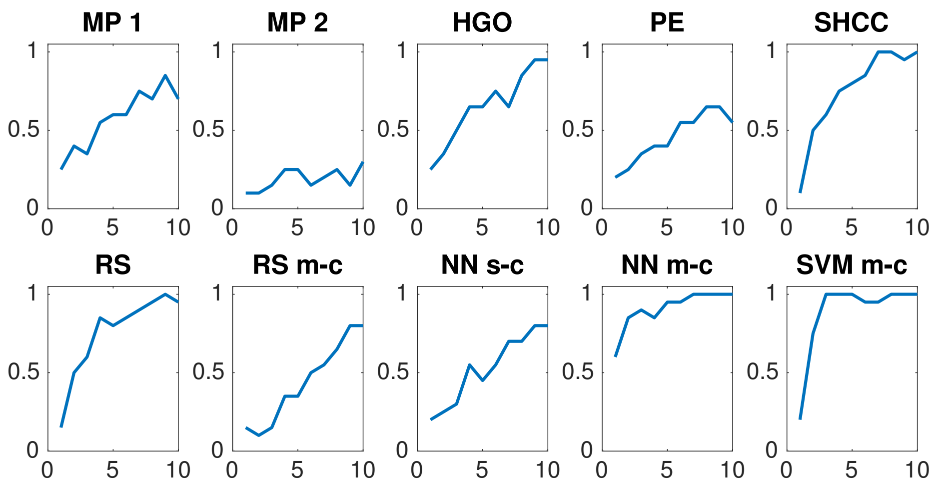

Figure 8. Performance obtained for all the methods. The amplitudes of the N1 and P3 component of the superimposed ERP are randomly reduced.

4. Discussion

Findings

The shape of the signal is absolutely related to the single trial latency. However the methods are more robust to changes in peak amplitudes.

The multichannel approach provides better information, except for the raw signal.

The conventional clinical method of observing the waveform is understood to be subjective and laborious because results depend on the technicians' experience and expertise. The need for more objective measurements pushed the adoption of more automated means of decoding the signals and demanded a need for replication [13]. This lead to the initial development of quantitative EEG, which however didn't replaced clinically the traditional approach which is still widespread.

This approach is relative common in chemical analysis (i.e. chemometrics Skoog, D.; West, D.; Holler, F. Analtyical Chemistry, An Introduction; Saunders: Philadelphia, 1994.), geology (sismic analysis), and quantitive financial analysis. EKG, or Electrocardiogram, on the other hand, has been extensively processed and analyzed by waveform methods. P,Q,R,S,T peaks in EKG analysis (REFERENCE). Additionally, the same problem can be found in Intelligent Character Recognition.

Dimensionality reduction which is truly applied when the waveform is actually formed (curse of dimensionality).

Segmetation or identification is not considered. Where should I look from within the EEG trace ? This is clear the problem of detection and not feature extraction.

5. Conclusion

The purpose of this work was twofold, (1) raise awareness about the utility of using automatic waveform-based methods to study EEG signals, (2) to provide an overview of the state-of-the-art of those methods, and (3) to compare those methods and verify if it is possible to obtain classification accuracies based exclusively on the signal's waveform.

Invasive methods remains an issue (referencia del paper de nature que muestra como causan deficits los implantes)

BCI as Assistive technology and BCI supplement natural motor output The value of clinical focus, BCI reliability (WOkpaw and wolpaw). Clinical EEG diagnosis may support a vast set of already understood knowledge which is based on identifying EEG patterns by their shape and that can lead to more robust implementation of BCI devices.

Let us now turn to the question posed in the title of this paper.

Successful approaches in Computer Vision or pattern recognition in other areas use a set of different features to compount ensemble classifiers. All these methods had the advantage that they can truly map a visual component with a clinical meaning, assessed by a physician, and provide an automatic identification which can be constructed by the set of methods. We believe this approach can be used to provide tools which are more meaningful to the clinical set.

Particularly considering BCI, this approach, in line with the general idea, can be used to foster BCI solutions that can help clinical settings. Precisely for the same reasons.

More work has to be conducted in order to extend this methods to other patterns of waves.

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Abbreviations

The following abbreviations are used in this manuscript:

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

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