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 approach which is based on using digital tools 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. The purpose of this work is to help to start to fill this gap by doing a review and description of the automatic methods that have been used to detect patterns in the waveforms, and to perform a benchmarking analysis to determine different characteristics of those methods that aim to detect specific waveforms mimicking what physicians has been doing since the inception of this fruitful technology.

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

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0. Introduction

Current society is demanding technology to once and for all provide the means to realize the utopia of social inclusion for people with disabilities. Additionally, a worldwide aging population is also claiming for solutions to extend active lifestyles throughout all life, including additional years that medicine is allowing humanity to have [1]. At the same time, the digital gadgets and the digital revolution have modified the way people interact with all their devices. A new emerging digital society is consolidating and smart wearable sensors are starting to be used routinely to obtain bio-signals, in an active or passive way (Wolpaw Communication and control) Although this communication is based on muscular movement [2], all these trends are precisely 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 to a machine is currently being under development: Brain Machine Interfaces. Moreover, as long as computers are being used inside every machine that humanity posses [3] this discipline is specializing as Brain Computer Interfaces (BCI) or Brain-Neural Computer Interfaces (BNCI). On 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) [4].

EEG sensors are wearable [5] non-invasive, portable and mobile [6], with excellent temporal resolution, and acceptable spatial resolution [7]. This humble diagnosis device has been transformed into currently the best approach that we posses to precisely detect, out-of-the lab in an ambulatory context, information from the Central Nervous System and to use that information to volitionally drive our cars, steer our drones, write our emails, and control our wheelchairs [8].

The clinical and historical approach to analyze EEG signals were based on detecting visual patterns out of the EEG trace or polygraph (Atlas of EEG patterns): multichannel signals were extracted and plotted over a piece of paper, continuously. Electroencephalographers or Electroencephalography technician have decoded and detected patterns along the signals by visually inspecting them [4]. Even nowadays clinical EEG remains a visually interpreted test [7].

Automatic processing, or quantitave EEG, was based first on analog electronic devices and later on computerized digital processing methods [9]. They implemented mathematically and algorithmically complex procedures to decode the information with outstanding success [8]. The best materialization of the automatic processing of EEG signals lays in the BCI discipline, where 71.2% is based on EEG [2].

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 an 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 aim to outline a better understanding of the different approaches. 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 [10,11].

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 Electroencephalogram is one of the most widespread used device to capture brain signals. It 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* [9]. 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 EEG research explosion 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 highly complex. It can be modeled as a linear stochastic process with great similarities to noise [12]. They are measured in microvolts, and those slightly variations are contaminated with heavy endogenous artifacts and exogenous spurious signals.

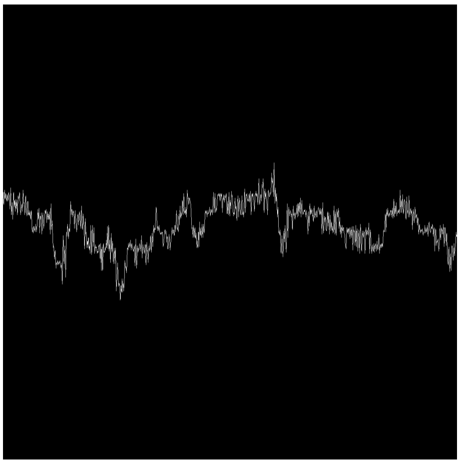

Figure 1. Sample EEG signal captured and plotted on a 2D image using the popular and commercial EPOC Emotiv using EEGLAB.

The device that captures these small variations in the current potentials over the scalp is called the Electroencephalograph. An explanation on the particularities and modelling of EEG can be obtained from [13], as well as in the description of the electrophysiological aspects of the method [14].

EEG signals have the following general components:

- Artefacts: endogeneous exogeneous as well as physiological or non-physiological (EEG MEG REview).
- 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 [9].
- DC drift and trending
- Basal EEG activity
- Inter-subject and intra-subject variability:It is known that EEG can be affected by the person behavior like sleep hygiene, caffeine intake, smoking habit, alcohol intake before EEG [15].

Overall, EEG can be characterized by their phase, amplitude, frequency and *waveform*.

- 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 activty

Understood according to the belongings or not to a repeated rhythm.

- 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.

Additionally, the number of electrodes and their positions over the scalp determines a **Spatial Structure**: waveforms can be generalized, focal or lateralized (EEG).

Finally, indexes can be derived as CFC, Cross Frequency Coupling, Phase-Amplitude Coupling, Phase-Phase Coupling.

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 [16] . The EEG research has focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG *graphoelements* [4].

Sleep Research has been studied in this way by performing Polysomnographic recordings (PSG) [17], 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 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, in Epilepsy EEG data acquisition is crucial during the assessment of patients with focal epilepsies for potential seizure surgery, where the origin of the seizure activity must be reliably detected. The determination of the Epileptic Seizure onset is defined as the first electrical change seen in the EEG rhythm as compared to baseline or any clinical sign indicating seizure onset (Clinical EEG). Most epilepsy patients also show characteristic interictal (or between-seizure) epileptiform discharges (IEDs) termed spike (<70 microsec duration), spike and wave, or sharp-wave (70–200 microsec duration) discharges. (Electroencephalography Introduction Canadian Epileptic Assosiation). All these characterization are strictly based on the waveform shape.

Finally, there are specific EEG patterns that can be used to determine Depth of anestisia and aEEG, amplitude integrated electroencephalography or cerebral function monitoring (REFERENCE) is used to determine coma levels based on shapes obtained from shapes observed in the EEG.

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 called EEG biomarker, EEG pattern, signal shape, signal form and a morphological signal (CITAS DONDE SE LAS LLAMA ASI).

Waveform characterization pays importance to context, both in a spatial and in a temporal sense (Jensen). On the basis of contextual consideration, some specific waveform can be considered as noise while in other context is precisely the element which has a cognitive functional implication.

Shape or waveform analysis methods are considered as nonparametric methods (in opposition to statistical or dynamical models). They can explore the amplitude, energy or more complex like the teager energy operand and L-Z Lempel-Ziv complexity measurement (thakor qEEG).

Slight variations in weather slopes or other features are scored may be important to certain applications.

It has

- characteristic shape, or waveform.
- rising phase
- falling phase
- pronounced plateau
- ripples and wiggles.

- Amplitude
- Arch
- Frequency
- Phase
- Nonsinusoidal sinusoidal

- Oscilation
- Sawtooth: motor cortical beta oscillations
- Sharpness
- Spike-wave discharge
- Transient event

Other characterization include, subjective definitions of sharper, arch comb or wicket shape, sawtooth, rectangular, spike-wave like, decay phase, voltage rise, peaks and troughs, short term voltage change around each extrema in the raw trace, peak and trough sharpness ratio, symmetry between rise and decay phase, slope ratio (steepness of the rise period to that of the adjacent decay period. For instance, descriptions like "Central trough is sharper and more negative that the adjacent troughs" are common in the literature.

- Attenuation (synonyms: suppression, 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. (Note: term is used in interpretative sense but as a descriptor of change in the EEG).
- 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.
- Sinusoidal. Waves resembling sine waves. Monomorphic activity usually is sinusoidal.
- Transient. An isolated wave or pattern that is distinctly different from background activity.

2. Materials and Methods

In order to determine which processing method to be considered as a "waveform template matching" we restrict ourselves to the following criteria:

1. The pattern can be identified and verified by visual inspection.
2. The pattern matching is performed in time-domain.
3. The analysis take account the shape of the plot of the signal.
4. The feature extraction procedure allows to create a Template database.
5. A Single Channel Processing approach.

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.

2.1. Selected Algorithms

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

Although the term morphology has been used to identify this approach, We specifically excluded Mathematical Morphological based methods [18]. 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).

2.2. Excluded Methods

2.2.1. Waveform features

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 [19,21]. Straightforward in its implementation, it consists in selecting a component, particularly a simple component based on the expected location of its more prominent deflection [20]. Particularly common in ERP Research, the name of many of the EEG features directly reference 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 [22] 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 [24**?**]. Additionally, a logarithmic graph of the peak-to-peak amplitude or aEEG [**?**] is used nowadays in Neonatal Intensive Care Units.

Other works on EEG explored the idea to extend human capacities analyzing EEG waveforms (automatic detection of k complexes), (A Waveform Analyzer Applied to the Human EEG) where a feature from amplitude and frequency of its signal and its derivative in time-domain is used.

Althought CASENET REFERENCe explored "waveform" structure they were purely based on spike detection based on feeding artificial neural networks.

(fujimori, PAA, etc). Uchida 1999

2.2.2. Averaging Methods

The methods that allow to identified waveforms are used to determine different alignments while averaging epochs.

This long-standing problem has been tackled from different perspectives. Woody's Template Matching is perhaps the best effort as well as Pham, and Tuan and others EML.

Dictionary, template based method. Many do not consider the waveform, albeit they do use a set of templates obtained from a dictionary.

Cross Covariance with Template or Cross Correlation or ACF: Autocorrelation Function: PHAM METHOD

Applying a FIR filter with templates

Krusienski et al 2007 Serby et al 2005

extended to wavelent analysis.

Dynamic Time Warping and other Warp Averaging methods were also used.

Wrapping Analysis

Warp averaging

2.3. Matching Pursuit

Pursuit algorithms refer, in their many variants, as blind source separation techniques that assume that the EEG signal is a linear combination of different sources that comes from template dictionaries.

We include them here because they are traditional in terms for the traditional view of Morphological Analysis or Shape domain analysis, though they do not restrict to our own definition of "shape domain processing".

However in terms of

2.4. Permutation Entropy

Bond and Pompe PE method.

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.

2.5. Slope Horizontal Chain Code

contour representation based on an adapted version of the Slope Chain Code (SCC)

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.

2.6. Histogram of Gradients

2.7. Merger of Increasing and Decreasing Sequences

Stepwise downsampling

2.8. Experimental Protocol

In order to verify each one of the approaches we will inject into a known dataset spurious p300 signal that we may be able to control. By implementing this pseudo-real approach, we can effectively control null-signals of this evoked potentials following the same approach of other similar works (ref Ouyang2017, el trabajo de estudio de templates y el trabajo de p3 y la tesis).

Jaskowski and Verleger (2000)

At the same time adding a mixed signal with varying degrees of SNR will allow us to determine robustness of the different methods.

We will extend this results to offline processing a public dataset of real P300 patterns.

The original signal-to-noise ratio was calculated as Hue 2010.

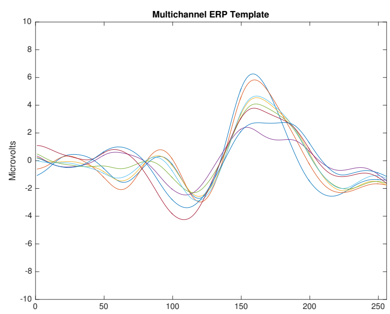

Figure 2. ERP Template obtained from the point-to-point averaging of a P300 component of a subject obtained from the public dataset.

2.8.1. Classification

In order to classify we will use the same classifier for every method. By doing this we will avoid

2.8.2. Parameters

Each method has its own set of parameters which are optimized. We will try to use an approach used in (matching pursuit paper for bci) where the best parameters are those which provide the best performance.

Hence, in order to obtain the right set of parameters for each method, an optimization problem was used fixing the injected signal to a gain of 3, and optimizing the parameters.

3. Results

Results are shown in Table 1 and in Figure 1. Table 1 shows the performance to identify each letter of the standard P300 Speller Matrix. Figure 2 shows how the performance increase when averaging is implemented.

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

Method	Single Trial Performance
MP	90
PE	89
SHCC	20

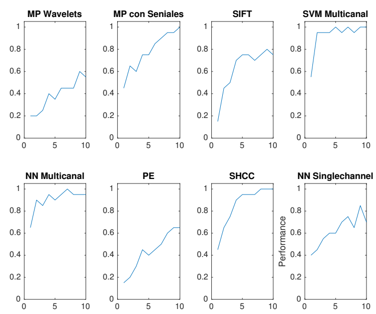

Figure 3. Performance obtained from the different methods.

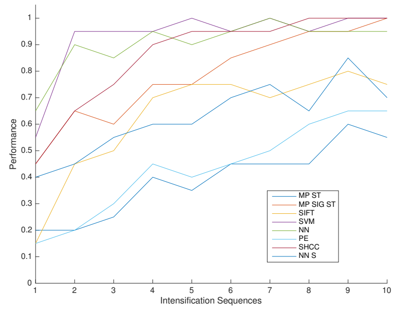

Figure 4. Performance obtained from the different methods while averaging different trials.

4. Discussion

In spite of all this, 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 [12]. 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)

Dimensionality reduction which is truly applied when the waveform is actually formed.

We left out the segmetation issue which is itself a huge problem. Where should I look from within the EEG trace ?

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 verify and compare those methods.

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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