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A literature review of spike detection problem in electroencephalogram

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Abstract
This work offers a preliminary study on methods for detection of spike in electroencephalogram (EEG) signals. The present research investigated recent studies on automated spike detection techniques. From 80 selected papers, we reviewed over 40 according to five indicators (year of publication, feature extraction and classification methods, performance evaluation and dataset). Since feature extraction plays a fundamental role in automatic spike detection, a comprehensive literature review indicated the wavelet-based methods as suitable approaches to address such task. In addition, we covered the main topics related to the theme, such as classifiers, data reduction techniques and performance metrics. This study provides directions to both conduct future studies and implement automated systems to assist in epilepsy diagnosis.

Keywords: epilepsy, EEG, automatic spike detection, feature extraction, spike classification

1. Introduction
A. Electroencephalogram
Origin of EEG
There have always been doubts as to whether the EEG actually originated in the cortex. When recording from the scalp of the patient with trephine holes in the skull, found that alpha rhythm was always greater when one of the electrodes was placed over hole, and greatest when needle pierced the scalp above the opening. This is the evidence that the EEG did not originated in the scalp.

There have periodically have been suggestion that waves such regular sinusoidal wave could be generated by nerve cells whose own electrical activity has always been regarded as always been exclusively spiky. In a group of cortical neurons, that the neurons depolarized almost simultaneously and that the gross EEG represents the envelope of underlying tissues. The gross EEG recorded from the other side of a centimetre of bone, skin, fat and cerebrospinal fluid, was thought to represent blurred picture of the sum of the activity of many individuals cells.

However implanted microelectrodes in the brain experimental animals and found that wave like EEG activity could. be recorded when the electrodes were only 30 um apart. Other suggestion may have been put forward by many reashers the EEG may be due to the slow changes in neurons in the underlying cortex kept in synchrony by generators in the thalamus. Neurologist does not really know exactly how the human EEG generated. There is no doubt however that electrical activity originating in the human cortex can be measured from the scalp.

The electroencephalogram (EEG) is the electrical activity recorded from the human scalp. The EEG is a fundamental tool in the diagnosis and research of several brain disorders, including those related to epilepsy [1]. As a non-invasive procedure to register the brain activity, combined with portable monitoring (i.e. not restricting the patient's mobility) and digital recordings (paperless registers), the scalp EEG has provided promising ways for computer-based signal processing to aid in epilepsy diagnosis (i.e. by identifying the epileptic focus before a surgical intervention or by helping with prescription drugs). The brainwaves recorded in an EEG are distributed in a few frequency ranges, corresponding to different brain states. These rhythms are categorized into main five frequency bands (Table 1). Typically, the wave amplitude measured from the scalp varies from 10μV to 100μV, but may it reach several millivolts in the case of spikes [2]. The brain's electrical activity is captured by using special electrodes disposed on the surface scalp (or a cap of electrodes). Each electrode is attached to one EEG register device's input channel, usually according to the 10-20 system [3].

Table 1

Rhythm	Frequency band (Hz)
delta (δ)	0.5 - 4
theta (θ)	4 - 8
alpha (α)	8 - 13
beta (β)	13 - 30
gamma (γ)	> 30

B. Epilepsy
Epilepsy is a neurological disorder that affects the nervous system with unknown causes in most cases. Epilepsy is also known as a seizure disorder. A seizure reflects a temporary disturbance of the brain functioning provoked by a sudden and intense hyper-synchronous electrical activity of the neurons [2, 4]. A practical clinical definition of epilepsy was recently published by The International League Against Epilepsy (ILAE, 14 APR 2014): "Epilepsy is a disease of the brain defined by any of the following conditions: (1) at least two unprovoked (or reflex) seizures occurring >24 h apart; (2) one unprovoked (or reflex) seizure and a probability of further seizures similar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years; (3) diagnosis of an epilepsy syndrome [5]." According to the International Bureau for Epilepsy (IBE), on average, one person in every 100 has epilepsy. The proportion of affected people comes higher in developing countries [4].

C. Spikes

Paroxysmal interictal events in EEG are distinctive signatures of epilepsy. Paroxysmal abnormality consists mainly of sudden high amplitude and sharp peaks (or spikes), and cerebral rhythm changes in EEG recording [6, 7]. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology (IFSECN) defines: "Epileptiform patterns (epileptiform discharge or activity): transients distinguishable from background activity, with a characteristic spiky morphology, typically, but neither neither exclusively nor invariably, found in interictal EEGs of people with epilepsy [8]." Thus, a spike is usually depicted in terms of its morphological characteristics, such as amplitude, duration, sharpness, and emergence from its background [6]. These epileptic spikes play a fundamental role in the diagnosis of epilepsy, providing important information to identify, classify and localize the epileptic focus.

A morphological decomposition of interictal waveforms may be comprised as sharp waves, spikes, spike-and-wave complex, polyspikes and polyspikes-and-slow wave complex.

The IFSECN [8] provides the following definitions

- **Sharp wave:** A transient clearly distinguished from background activity, with pointed peak at a conventional paper speed or time scale and duration of 70±200 ms, i.e. over 1/4±1/5 s approximately.
- **Spike:** A transient, clearly distinguished from background activity, with pointed peak at a conventional paper speed or time scale and a duration from 20 to under 70 ms, i.e. 1/50±1/15 s, approximately.
- **Slow wave:** Wave with duration longer than alpha waves, i.e. over 1/8 s.
- **Spike-and-slow-wave complex:** A pattern consisting of a spike followed by a slow wave.
- **Multiple spike complex:** A sequence of two or more spikes.
- **Polyspike-and-slow-wave complex:** A sequence of two or more spikes associated with one or more slow waves.

In this paper we opted to generalize the term "spike(s)" to refer to spike events and sharp waves.

D. Automated spike detection

Over the years, the automatic spike detection problem has been addressed by several methods. Naturally, given the developments in scientific and computing areas, new and more sophisticated approaches were suggested. However, the main strategies remain practically unchanged: (1) to segment a digitized EEG, so to extract discriminative features (e.g. morphological descriptors, statistical values and spectral characteristics) from the portion under processing and (2) to give a feature vector organized with such attributes to a classifier stage.

Several methods are available for analysing EEG signals, such as mimetic, morphological, parametric modeling, statistical analysis and template matching, to cite a few. Below we present a summary of these methods.

Mimetic This method tries to imitate the visual interpretation of EEG graph elements given by neurophysiologists. Based on the expertise of these professionals, to characterize a spike event, some waveform descriptors are graphically defined and/or calculated, such as slope, sharpness, duration, vertex angle and amplitude. The pioneer approach used by Gotman and Gloor [9] concerns to decompose the spike event in two half-waves. Around this idea, many analogous methods were developed (see section III-D).

Morphological *this* method intends to emphasize the epileptiform patterns by extracting latent information present in the EEG signal, such as the statistical behavior, frequency spectrum and time frequency components. To keep an accurate representation of the original signal, a careful analysis must be performed. In this context, we observed many approaches: morphological filters, spectral analysis, statistical and wavelet transformation methods.

Parametric Modeling, are *non-linear features* and *component analysis* are also common in spike detection studies. In section III-J, review studies covering these methods are listed. We opted to limit the scope to encompass the techniques more suitable for feature extraction. In combined approaches, methods based on template, parametric modeling and machine learning concepts may require a preliminary step of attributes extraction. We categorized these methods as hybrid techniques, since it is difficult to disjoint the mimetic or the morphological analyses from the spike detection task. An exception exists to raw-based analysis, since all samples (discrete points) inside the time-series segment are given as input to a classifier. As stated in [10], there is no concern about what parameters are more valuable than others.

The spike classification stage involves setting rules to evaluate spike candidates. Common approaches are based on thresholds and/or machine learning. Often, statistical analysis is applied to determine an adequate threshold. In the same way, artificial neural network (ANN) is usually employed as a general classifier. Based on different architectures and algorithms, an ANN is able to deal both with raw- and with feature-based methods.

1. **Literature review**

We performed an extensive literature review focused on automated spike detection methods, categorizing most of the relevant published works in accordance with five indicators:

- Year of publication, comprising studies published from 2014 to 2018;
- Feature extraction methods, focusing on specific techniques for spike detection in epileptic EEG recordings;
- Classification methods, including both threshold and machine learning;
- Accuracy (including sensitivity and selectivity) and
- Dataset, both for performance comparison.

We examined over 40 papers among 80 selected, emphasizing the search for appropriate techniques used of characteristics from EEG signals holds a significant role in spike detection problem [11, 13].

Studies covering methods designed for spike EEG (electrocorticography), spikes and seizure detection/prediction were discarded. Wilson and Emerson [14] provide a good overview of earlier researches, covering important aspects related to algorithms. Tzallas *et al.* [10] offer a recent review study, dealing both with spike detection and with seizure detection analysis.

The selected works are those that best fit our set of criteria.

A list of literature review studies on automated EEG analysis for epileptic spike and seizure detection, covering feature extraction methods, classification techniques and performance evaluation.

Table 1

Work	Year	Review focus
Acharya *et al*.	2013	Feature extraction methods
Tzallas *et al*.	2012	Spike and seizure detection methods
Nasehi and Pourghassem	2012	Seizure detection algorithms, dataset and performance evaluation measures
Song	2011	Seizure detection

2. Discussion

EEG analysis for automated techniques

The EEG analysis admits at least two main approaches for addressing the spike detection problem:

a) Raw-based, relating to the original EEG data;

b) Feature-based, relating to the extraction of discriminative characteristics from the raw EEG data.

2.1 Raw- vs. feature-based analysis

When EEG raw time series is directly given as the input to a classifier stage, there is no need to pre-process the signal. Disregarding any kind of morphological, statistical and spectral analysis, it is the entire responsibility of the classifier to identify the spike events from the original data. Acir *et al*. [35] pointed out that while the parameterized input approach has the advantage of using reduced size of data input, it requires a precise definition of how and which attributes should be selected. Pang *et al*. [11] performed a comparison between an ANN fed by features selected using three different methods and one fed by a raw EEG. They observed that both techniques yielded similar results. However, the authors remark that the selected attributes may not have had a good EEG signal representation. On the other hand, many studies have cited the results obtained by Webber *et al*. [60] revealing that the spike classification (ANN based) performed better (in terms of accuracy and speed) when dealing with parameterized data. A more recent work, proposed by Kutlu *et al*. [29] also obtained better results when using classifiers trained with extracted features. In 1997, James [61] raised the same discussion citing the attempts of some authors trying answer this question, emphasizing the paradoxical results found by Özdamar *et al*. [62] (raw data) and Webber *et al*. [60] (parameterized data).

Raw-based techniques have a main drawback: to restrict the detection task to classifiers based on machine learning (ML) (e.g. Bayesian and artificial neural networks). Also, in comparison with feature-based techniques, it demands more computational resources (memory and processing time) due to the fact that a high-dimensional input data is imposed to the detection system [29, 39]. The feature-based approaches put a challenge: to select the optimal features providing efficiency in terms of spike detection performance. Mimetic and morphological approaches are the two widely-used ways to extract features. Each one has its own issues and advantages [10, 14]. Anyway, selecting features properly determines the success of a detection system, which is in some sense a trial and error procedure [39].

2.2 Segmentation

Both approaches share the disadvantage of windowing the EEG signal before delivering a feature vector to the classifier. The windowing operation indicates that the acquisition of informative attributes depends on segmenting the signal into pre-defined intervals. Taking into account the nonstationary nature of EEG signals (i.e. their frequency spectrum vary through
time), the extracted parameters and modeled estimations from segmented signal may misrepresent their original characteristics [63]. Overcoming this problem requires an adaptive segmentation: the signal is divided into quasi-stationary segments (i.e. the variance of frequency spectrum over time is reduced) of variable length [64]. In the same way, methods of feature extraction based on Wavelet Transform may lack the requirement of stationarity [7]. Tzallas *et al*. [33] dealt with nonstationarity of the EEG time series using a parametric approach based on time-varying autoregressive model.

2.3 Contextual Information

Whatever the spike detection method is used, there seems to be a consensus on using contextual information (spatial and temporal). According to James [61], spatial information represent what is happening in other EEG capturing channels at the same time as a candidate spike, and temporal information is related to similar events with similar distribution elsewhere in the EEG. Dingle *et al*. [65] stated that was generally accepted that the only way to separate epileptiform from non-epileptiform waves is to make use of a wide spatial and temporal context. Webber *et al*. [66] used rules to correlate an event on spatially adjacent channels of EEG. Recent studies have also incorporated this approach with template-match methods [25, 3, 64, 67]. Combining knowledge-based rules with other methods is a common technique to add knowledge of neurophysiologists that adopt spatial and temporal rules [10].

2.4 Feature extraction

The relevancy of feature extraction in automatic detection and classification of epileptic spikes was highlighted by many authors. Song and Zhang [42] stated that for an effective epilepsy diagnosis model, appropriate methods to extract meaningful features are required. They argue that feature extraction is often applied to complex, high dimensional and multivariate data. In addition, such stage is effective for data compression and pre-classification. In order to both assure the performance of the diagnosis system and compensate for the loss of information, optimal extraction and selection of parameters are necessary. Lhotská *et al*. [64] described the extraction of informative features with the greatest possible discriminative ability as an important task in automatic signal analysis. Likewise, Tamil *et al*. [68] remarked that the adequate methods of feature extraction are essential to facilitate the representation and interpretation of the data. Suresh and Balasubramanyam [46] pointed the feature extraction to enhance the spike characterization and extinguish the unwanted background activity. Therefore, extraction and selection of features play a critical role in spike classification tasks.

In the feature extraction process, discriminative parameters are collected from the EEG time series signal. A usual approach is to scrutinize the EEG data bylooking for characteristics that stand out either the spike or correlated events associated with epilepsy [68]. Common techniques are based on time-domain and frequency-domain analysis. In the former case, the features extracted from the spike waveforms, such as duration, slope, sharpness and amplitude form the basis for the mimetic methods [19, 22], [23, 29, 35, 40]. In the latter case, the signal is commonly analyzed by investigating frequency bands related to various conscious states or mental activities [42]. Typically, the extracted features are the dominant frequency and average power in a given frequency spectrum [29, 36, 64]. Statistical analysis offers good tools for data exploring and helps to discover significant patterns and features. Many works have combined such analysis with a variety of spike detection methods [20, 22, 41, 48, 52], to cite a few. Using morphological techniques, both time-domain and frequency-domain inspection are suitable to provide meaningful features.

Despite the success (in terms of spike representation) presented by the aforementioned approaches, the extracted features lack of time-frequency resolution and they usually do not consider the no stationary nature of spike events in EEG signal [42, 50, 52, 6]. The frequency details are not observed using time-domain analysis, precluding any spectral evaluation. On the other hand, spectral analysis (i.e. power-spectra, based on Fourier Transform) is not appropriate for no stationary signals. Indeed, the time-frequency information is not directly obtained from the coefficients produced by the Fourier Transform [69]. In short, it does not provide correlation between the time-localization and the frequency changes [50]. According to Quiroga [7], EEG signals are known to be highly no stationary, meaning that characteristics of the time series, such as the mean, variance or power-spectra, change with time. The time-frequency inspection, the so-called multire solution analysis, is proper to reveal and aggregate features of the signal along the time-frequency domain.

2.5 Wavelet-based methods

Similarly to Fourier Transforms (FT), the Wavelet Transform (WT) is a powerful tool for wave analysis. FT expands signals in terms of sinusoids based on frequency changes and is more suitable for periodic and linear time-invariant signals. On the other hand, the WT performs signal decomposition in terms of scaled (scale factor) and translated (time-shift factor) versions of a mother wavelet and a scaling function. The WT admits two main approaches for signal inspection: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). A wavelet (or waveform template) is an arbitrary small wave of limited duration and concentrated energy, designed to afford analysis of no stationary signals and transients. Several wavelet families are available for both DWT (e.g. Daubechies, Coifman) and CWT (e.g. Mexican Hat, Morlet). Hence, the WT is able to decompose the signal under analysis in expansion coefficients (sub-bands), which retains the time-frequency information. This two-dimensional representation allows recovering the original time localization relative to a specific spectral component. Even under the scale concept, the frequency remains related to WT coefficients [70]. A smaller wavelet scale factor compresses the wavelet in time. This indicates that the WT coefficients will represent the signal at a high frequency (finer scale in terms of time resolution). Conversely, as a larger scale factor expands the wavelet in time, the WT coefficients will represent the signal's low frequency components (finer scale in terms of frequency resolution) [71].

4. Final remarks

We emphasized the approach on Wavelet Transforms due its evidenced efficiency extracting features from no stationary signals, allowing simultaneous analysis in time and frequency domains. However, particular attention must be paid to selecting the wavelet basis, since meaningful attributes are only revealed when there is a sufficient degree of correlation among the wavelet and the inspected data. CWT offers finer resolution than DWT at the expense of computational resources. WPD may establish a middle ground between the decomposition resolution and the computing demand. Despite of all the WT benefits, combining strategies is a common practice in most reviewed studies. Also based on signal decomposition, Hilbert-Huang transform is a recent methodology addressing the spike detection in EEG, providing opportunity for innovative studies.

Concerning to supervised ML classifiers, at least two main items should be prioritized: (1) a large dataset, in order to supply sufficient data for training and testing steps; (2) the relevancy of extracted features, since weak discriminative features lead the classifier to perform poorly.

The analysis provided in section III avoids comparisons in terms of accuracy. Despite the unquestionable importance of performance evaluation, this kind of measure tends to be subjective, since there is even no unanimous agreement among the experts about the spike classification [66] and the dataset heterogeneity does not allow a direct comparison. Table shows that most of the studies achieved good results in terms of spike detection performance, but it is not possible to evaluate some computational aspects (e.g. memory consumed, processing time) and the algorithm feasibility for real time processing. Such information is essential when developing a field application.

The development of robust and trustworthy automated (automatic or semi-automatic) systems and algorithms for spike detection remains itself an open challenge. But, the current availability of computational resources (e.g. high-speed networks for data transfer, low-cost data storage and massively parallel computing), combined with the advances in mathematical and DSP techniques, encourage the development of systems both for real-time patient monitoring and for assisting in epilepsy diagnosis.

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