Automated Detection of Interictal Spikes in EEG: A literature review

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Abstract. This work offers a preliminary study on methods for automatic detection of interictal epileptiform discharges 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, artifact rejection, data reduction techniques and performance metrics. This study provides directions to both conduct future studies and implement automated systems to assist in epilepsy diagnosis.

Key words: epilepsy, EEG, automatic spike detection, feature extraction, spike classification

I. Introduction

A. Electroencephalogram

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 noninvasive 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).

Table 1- Brain rhythms

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

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].

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. Interictal events are epileptiform discharges that occur between seizures and characterize an epileptic symptom. 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 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.

The *mimetic* method tries to imitate the visual interpretation of EEG graphoelements 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).

The *morphological* 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.

Techniques based on *template match*, *parametric modeling*, *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.

E. Document organization

This document is arranged as follows: a literature review is presented in Section II. Section III provides a discussion about the spike detection methods – focusing on features extraction using wavelet transformation – and the issues related to the automated EEG analysis, such as artifact rejection, optimal feature selection, performance evaluation and dataset. In section IV, we present the final considerations.

II. 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 1999 to 2014;
- feature extraction methods, focusing on specific techniques for interictal 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 for interictal events recognition, especially those based on feature extraction, since a proper extraction of characteristics from EEG signals holds a significant role in spike detection problem[11]–[13]. Studies covering methods designed for intracranial EEG (electrocorticography), ictal 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. Table 2 stands out the key details of the classified manuscripts, allowing us to contrast the exploited methods conjointly with their issues more easily. Since the methods based on Wavelet Transform hold a large percentage of usage (~40% in our literature review sample), Table is partitioned following this observation. Despite the fact of that the literature review prevails on papers listed in Table , additional studies complement our research. Indeed, Table 2 shows a summary of common methods for automatic spike detection, describing the strategies behind each one.

Table 2 - Spike detection methods from literature review†

Ref. No.	Year	Feature Extraction Method	Combined Method (Feat. Extraction & Detection)	Detection/Classification Method	Accuracy[%] (best result)	Dataset [#EEGs, duration, #IEDs]
		Non wavelet-based				
[15]	2014	--	Ref. to [16]	Ref. to [16]	95	Ref. to [16]
[17]	2014	Morphological(4 features)	--	FF/BP ANN 4-5-1	99.11	*
[18]	2013	Morphological(window functions)	SNEO	Adaptive threshold	--	Synthetic EEG; *
[19]	2013	Mimetic(13 descriptors)	k-point NEO & Calculated features	Adaboost classifier	90	15, --, 142
[20]	2013	Statistical features	Linear Discriminant Analysis	Fisher's Linear Discriminant	Sen.: 98.45 Sel.:96.06	*
[16]	2013	--	SVM	Template-match	--	15, 306 min, 241
[21]	2012	--	Clustering (morphologic)	Spike's centroid correlation	Sen.:93.7 Sel.:93.7	17, long-term, ~25.000
[22]	2011	Mimetic(45 descriptors)	Statistical & Entropy features	ANN	Sen.:95 Spe.:76	7,--,--
[23]	2011	Mimetic(4 waveform descriptors)	Clustering & averaging	Template-match	--	2,96 min ,--
[24]	2011	Morphological filter	Parametric(parabola models the EEG)	Threshold	--	15,~60min/pat,--
[25]	2011	Mimetic	Clustering	Template-match	--	--
[26]	2010	--	Amplitude threshold	Template-match	--	--
[27]	2009	--	Parallel Computing	Ref. to [28]	Ref. to [28]	*
[29]	2009	Mimetic(6 waveform descriptors)	Feature Transformation(4 methods)	MLP ANN	90	--,--,39
[28]	2008	--	--	DFA(morphological-based)	95.68	*
[30]	2008	--	Mean Squared Error threshold	Template-match	96	2,--,124
[31]	2008	--	Spatio-temporal information	Template-match	Sen.:92 Sel:77	8, 130 min, --
[32]	2007	Morphological (filter)	Feature Optimization	Threshold	--	12, --, 957
[33]	2006	Parametric	TVAR(Kalman filter)	Threshold	--	Synthetic EEG; 1, --, --
[34]	2006	Morphological (filter)	--	Threshold	91.62	Synthetic EEG; 9, --, 739
[35]	2005	Mimetic(6 waveform descriptors)	Pre-classification & Multichannel	RBFN ANN	Sen.: 100 Sel.: 89.1	29, ~21min/patient, 309
[36]	2005	Morphological(5 features)	Feature combination	Elman ANN	99.6	(4)
[37]	2004	Parametric(time-frequency)	Matching Pursuit	Parameters fit	Sen.: 92 Sel.:0.84	(3)
[38]	2004	Mimetic(10 criteria)	Walsh Transform	Criteria fit	Sen.:79 Sel.:85	18, 20~30min/pat,139
[39]	2004	Parametric(Nonlinear Filter)	Peak detection	Post-Classification/SVM	Sen.:90.3 Sel.:88.1	25,--,--
[40]	1999	Mimetic(7 waveform descriptors)	SOFM ANN	Fuzzy (Spatial Combiner)	Sen.: 55.3 Sel.:82	43, --, >3000
		Wavelet based				
[41]	2013	Db4(statistical features of 5 bands)	Mimetic & Spectral analysis & Spatial Information	Bayesian classifier & MLP/FF ANN	Sen:47.3 Spe:85.9	100,30sec/pat,2571
[42]	2013	Db4(5 bands)	Complexity measures(raw) & GA	FF ANN(ELM)	94.8	(4)
[43]	2013	SWT Db8(1 approximation band)	Parametric model(TVAR)	Threshold	--	Synthetic EEG; 1,5sec,--
[44]	2013	Db1(MTE of CD5)	Optimal feature selection	ANFIS	100	250,0.4min/pat,--
[45]	2013	--	Optimizes Wavelet resolution	Double Threshold	Sen.:78 Spe.:96	105,~175min,--
[46]	2012	Db4(3 bands)	Energy estimation(raw, using SNEO)	BP ANN & Logical ANDed(raw)	--	--

Ref. No.	Year	Feature Extraction Method	Combined Methods (Feat. Extraction & Detection)	Detection/Classification Method	Accuracy[%] (best result)	Dataset [#EEGs, duration, #IEDs]
[47]	2012	Parametric(Non-linear filter)	Wavelet transform	Threshold	100	10,--,178
[48]	2012	WPD (4 levels, 16 sub-bands)	Statistical (ApEnt & Energy)	BP ANN	85.2(spikes only)	100,23.6sec/pat,--
[49]	2011	Db4	Wavelet basis chose using GA	Threshold (coefficients selection)	Sel.: 100 Sen.:100	(3)
[50]	2010	Db2(4 sub-bands)	Component Analysis(PCA)	ANN (5 different architectures)	100(using GRNN)	3,--,--
[51]	2008	Db4(6 sub-bands)	Energy (raw, spike portion)	Adaptive Threshold(2 sub-bands)	90.5	22,3sec/pat,687
[52]	2008	Db2(4 sub-bands)	Statistical analysis(4 features)	MLP ANN (2 levels)	94.83	(4)
[53]	2006	Coiflet1(4 sub-bands)	--	ANNs	Sen.:70.78 Spe.:69.12	7,12h,>6721
[6]	2003	Mexican Hat Wavelet(3 scales)	Normalized wavelet power	Threshold	Sen.:70 Sel.:67	--,--,340
[54]	2002	CWT(Morlet)	Wavelet scale selection	ANN	Sen.: 82.6 Sel.:90.4	1,--,--
[55]	2002	CWT(Marr wavelet, 32 sub-bands)	Waveform feature(CD), spatial & temporal contexts	ANN	90	81,>800h,--
[56]	2000	CWT(psi-1 wavelet, 4 sub-bands)	--	Threshold	Sen.: 84 Sel.: 12	11,278min,298
[57]		--(3 sub-bands)	SNEO	Threshold	--	Synthetic EEG; 36,--,--

Acronyms: **IED:** Interictal Epileptiform Discharge; **ANN:** Artificial Neural Network; **FF:** Feed-Forward; **BP:** Back-Propagation; **MLP:** Multi-Layer Perceptron; **RBFN:** Radial Basis Function Network; **GRNN:** General Regression Neural Networks; **SOFM:** Self-Organizing Feature Map; **ELM:** Extreme Learning Machine; **SNEO:** Smoothed Nonlinear Energy Operator; **MTE:** Mean Teager Energy; **TVAR:** Time-Varying Auto Regressive **SVM:** Support Vector Machine; **DFA:** Deterministic Finite Automata; **GA:** Genetic Algorithms; **ANFIS:** Adaptive Neuro-Fuzzy Inference System; **WPD:** Wavelet Packet Decomposition; **[C/S]WT:** Continuous/Stationary Wavelet Transform; **CD:** Coefficient Detail; **ApEnt:** Approximate Entropy; **Sen:** Sensibility; **Sel:** Selectivity; **Spe:** Specitivity;

†: only selected papers are listed; **--:** not available, not evaluated or unclear; ***:** non-human dataset; (1) (2) Refer to [53], [58]; (3) Refer to [6]; (4) Refer to [59];

Table 3 - Summary of common spike detection methods based on our literature review and other studies [4], [5] and [58].

Methods	Data input	Strategies	Data Output	Combined Methods
Raw	Raw	To preserve the original data	Raw	Threshold, LM classifier
Mimetic	Raw*	Visual analysis (half-wave approach, slope, duration, amplitude)	Descriptors	Spatial context; Threshold, LM classifier
Morphological	Raw*	Morphological filters, spectral analysis, time-frequency analysis, statistical analysis	Features	Spatial context; Threshold, LM classifier
Template	Raw*/Descriptors/Features	Manual selection of epileptiform events, detection based on correlation	Templates	Contextual Information, Threshold (correlation)
Parametric	Raw	Linear and Non-Linear Estimation	Model	Spatial context; Threshold (error)
Clustering	Features/Templates	To separate spike candidates by classes	Classes	--
Component Analysis	Features/Descriptors	Linear/Independent/Principal Component Analysis	Optimal Features Selection	Threshold, LM classifier
Threshold	Raw*/Features/Descriptors	Adaptive or static, usually based on statistical analysis	Spike detection: YES/NO	Temporal context
Learning Machine Classifiers	Raw*/Features/Descriptors	Neural Network, Data Mining, Support Vector Machine classifiers	Spike detection: YES/NO	Temporal context; LM classifier, Fuzzy system

*Segmented/windowed portions of the EEG signal.

III. Discussion

A. 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.

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 preprocess 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. 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.

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], [31], [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].

B. 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 nonstationary 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 nonstationary 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 nonstationary, 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 multiresolution analysis, is proper to reveal and aggregate features of the signal along the time-frequency domain.

C. 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 nonstationary 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].

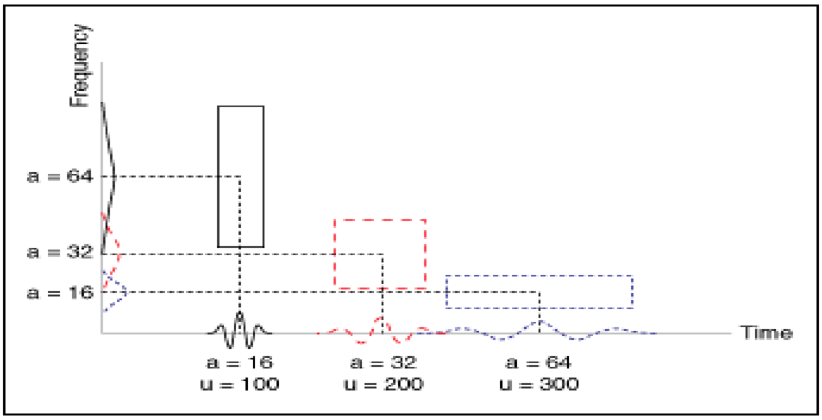

Figure 1- The fine frequency resolution of large-scale wavelets enables the measurement of the frequency of the slow variation components in a signal. The fine time resolution of small-scale wavelets enables the detection of the fast variation components in a signal (a - scale factor, u - time-shift). (National Instruments, [72]*)*

The paragraph above intends to give a general idea of wavelets. The fundamentals of WT theory and mathematical approaches are not covered in this work. For now, we present the main remarks on WT-based spike detection applications. Techniques based on WT are widely employed when it is necessary to inspect the signals for time and frequency analysis [56]. The main benefit using WT for EEG analysis relies on its multiresolution ability. This approach provides useful perspectives for EEG signal processing, such as data compression, de-noising and feature extraction [40], [56]. By using WT, it is possible to decompose the EEG signal in sub-bands, capture frequency and time information from low and/or fast transients and disregard the signal's nonstationarities [42].

In Table , WT appears as the main method in the front-end of the spike detection task. In most cases, the WT coefficients provide the features for posterior classification, but always supported by complementary techniques. This evidence corroborates that stated by Halford et al. [41]: the WT coefficients must be set out to an appropriate vector of features before being presented for classification. An important concern about the extraction of features based on WT is that the quality of the features depends highly on "mother" wavelet form, namely the basis function that best correlates to the spike's morphology and the signal's frequency components. Many authors pointed out that the wavelet basis choice is critical to achieve relevant features [41], [49]–[53]. The number of decomposition levels (sub-bands) is also very important to ensure that the WT coefficients carry out representative values [42], [44], [52]. In other words, the coefficients must discriminate the spike-like events of the signal and be useful for further analysis (e.g. post-processing and classification steps).

1. Mother wavelet selection and levels of decomposition

Regarding the Discrete Wavelet Transform (DWT), the coefficients can be computed using a filter bank structure composed by pairs of low-pass and high-pass filters. Such structures may decompose the original signal into sub-signals. Each level of decomposition corresponds to a down-sampled filter stage output, where the low-pass and high-pass filters produce approximation coefficients (A) and detail coefficients (D), respectively. The first level is generated from the original signal 'S' (see Figure 2). The subsequent levels are produced from the precedent approximation sub-bands [56]. In DWT, the WT coefficients are obtained by discrete translating and scaling operations[69].

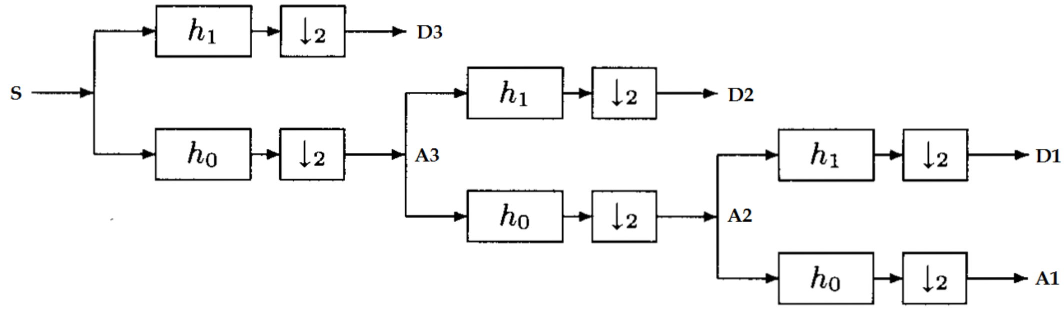

Figure 2- Three-Levels Two-Band Filter Bank (Burrus et al. [70]*)*

As listed in Table , the Daubechies order 4 (Db4) is the most recurrent wavelet basis (50%, 5 out of 10 works). Halford et al. [41] selected this wavelet to decompose the EEG raw data. Based on other researches, they argued the Db4 wavelet yields the highest correlation coefficients with the epileptic spike among the wavelet bases available in the MATLAB Toolbox. The signal decomposition was performed over a 64-element rectangular window applying 4 levels, yielding 5 detail sub-bands (D1-D4) and one approximation sub-band (A4). Following the work of Güler and Übeyli [73] and Jahankhani et al. [74], all sub-bands are taken into account to extract 4 statistical features by sub-band. In addition, they combined mimetic, spectral analysis, and spatial information features before giving the feature set to the classifier stage.

Song and Zhang [42] remarked some characteristic of Daubechies wavelets family, such as orthogonality and effective filter implementation. They cited some precedent works to justify their choice for Db4 : (a) according to Adeli et al. [69], the Db4 is thought to be the most suitable for EEG analysis; (b) Subasi [75], after testing different wavelet bases, pointed out the Db4 one being more appropriate for identifying changes in EEG data because of its smoothing features. In order to cover the EEG representative frequency range (0-60 Hz), they divided the EEG signal into 5 bands (delta, theta, alpha, beta, and gamma). Applying four levels of decomposition, they obtained the five sub-bands mentioned above. The complexity measures such as sample entropy, Hurst exponent and permutation entropy provide complementary information to set the feature vector. An optimal feature subset is selected by using genetic algorithm.

Suresh and Balasubramanyam [46] proposed a feature extraction scheme using Db4 wavelet to decompose the EEG records in 3 sub-bands. Their technique is based on the observation that spikes when analyzed with a filter bank (the DWT has such behavior intrinsically), spreads events in all sub-bands. In the other hand, the healthy brain signals and non-epileptic events are prone to have only low frequency components and appear only in low-resolution details. The sub-bands D1 to D3 and energy estimation parameters are presented as input to the spike detection stage.

Haydari and Soltanian-Zadeh [49] applied genetic algorithm for wavelet basis optimization (shift and scale parameters). They chose the Db4 wavelet to be the general basis form because of the resemblance to the common shape of an epileptic spike. From the optimized wavelet, the WT coefficients are selected by a threshold.

Indiradevi et al. [51] computed the cross-correlation between a given epileptic spike and different mother wavelets available in the MATLAB Toolbox. They found in Db4 wavelet the highest correlation coefficient. The EEG data was decomposed into 6 sub-bands to reach the desired frequency resolution. They selected the sub-bands 4 and 5 (details D4 and D5, frequency scope 4-16Hz) in order to reduce the effect of non-epileptiform fast transients like myogenic artifacts.

The Daubechies order 2 (Db2) was selected by Sezer et al.[50] and Übeyli [52]. Sezer et al. [50] did not provide a clear justification for their choice. The WT coefficients were taken from D1 to D4 details and A4 approximation sub-bands. Originally, they populated the feature vectors taking into account all decomposed levels, exception for D1 detail since it held values close to zero. At last, Principal Components Analysis (PCA) optimized the feature vectors size, reducing to 32 features.

Übeyli [52] justified her choice arguing that the smoothing features of Db2 made it appropriate to detect alterations in EEG time series. Also, she explains that the number of decomposition levels depends on the dominant frequency components of the signal. Also, the generated WT coefficients must correlate with the signal frequencies under analysis. She applied 4 levels of decomposition and presented features from D1 to D4 details and A4 approximation sub-bands for classification.

The Daubechies order 1 (Db1) wavelet was preferred by Gopan et al. [44]. They argued that Db1 provided maximum efficiency in comparison with other wavelet basis. In order to separate the brain rhythms, they applied 5 levels of wavelet decomposition. Only the D5 sub-band was used for classification.

Argoud et al. [53], after investigating over 40 mother wavelets obtained two types of basis that satisfied a set of pre-defined criteria. They found the Coiflet wavelets (order 1 and 2) more suitable for decompose the EEG signal. From Coiflet 1 application, the spikes and sharp waves were distinguished through D2 and D3 sub-bands. The high-frequency noise artifacts were accentuated using D1. On the other hand, to handle with the ocular activity issue, they used D4 from Coiflet 2 wavelet.

Radmehr and Anisheh [43] applied a variation of DWT, the Discrete Stationary Wavelet Transform (DSWT). Different from DWT, this approach pads the detail and approximation sub-bands with zeros (for each low-pass and high-pass filter) to keep unchanged the original data size (the segment length from a windowed EEG raw data) and provides a shift-invariant analysis. Thus, they pointed out the benefit from preservation of time information at each level of WT decomposition. The Daubechies order 8 (Db8) was selected as wavelet basis with no clear reason. Only the approximate sub-band was exploited from one-level wavelet decomposition. In their work, the WT acts as a pre-processing stage before modeling it by Time-Varying Autoregressive Model (TVAR).

The Wavelet Packet Decomposition (WPD) provides better resolution and clarification of details than that given by DWT. This tool decomposes both the low frequency components (approximations) and the high frequency components (details) [76] . Artameeyanant et al. [48] chose a Daubechies mother wavelet of unspecified order. By using WPD, the signals under analysis were decomposed into 4 levels, producing 16 sub-bands. From each sub-band, approximate entropy and energy of WT coefficients populated a feature vector.

Concerning to Continuous Wavelet Transform (CWT), the WT coefficients are computed by continuous scaling and translating. The term continuous is related to the scale increment, not to the data nature. The CWT is performed on a discrete signal. Liu et al. [55] selected CWT instead of DWT by reason of the finer scale achieved by the first approach while the last one has a coarser increment (usually scales itself by a factor of two between two adjacent levels). By separating the signal into 32 sub-bands, they applied different thresholds in three ranges of decomposition levels: spikes (index 0 to 7), sharp-waves (index 4 to 11) and, slow-waves (index 24 to 27) in order to generate a preliminary classification. From each group, the waveform features (mimetic approach) of wavelet coefficients were given as the input to the classifier stage. Thus, each feature vector is individually processed according their range. They chose Marr wavelet as the wavelet mother.

Goelz et al. [56] selected the CWT to overcome an important drawback present in DWT: the lack of shift-invariance. In practical terms, it means that identical events in a signal, but shifted by a couple of samples in time, may produce different coefficients at different levels of decomposition. They remarked that although the DWT allows transient events to be examined, a transient-specific feature may not be identified. The authors selected the psi-1 wavelet and 4 levels of decomposition to extract epileptiform features from the original signal. By averaging the WT coefficients across the four scales and 16 bipolar channels, the spike events are emphasized. Thresholds determine the candidate events as spike or as artifact.

Nuh et al. [54] selected Morlet wavelet and three scales to inspect the signal. The spike detection mechanism, based on artificial neural network (ANN), incorporated the feature extraction stage as the input layer.

Latka et al. [6] just argued that the Mexican Hat wavelet is particularly suitable for studying epileptic events. They used the normalized wavelet power instead of the WT coefficients and employed different thresholds across scales to identify spikes.

2. Remarks on wavelet transform application

To evaluate which WT approach is more appropriate for feature extraction or to be applied as complementary method (preliminary spike-like separation, artifact rejection or any pre- and post-processing step) is not a trivial task. We have seen that the choice of the mother wavelet is a trial and error process, and nonconsensual among the researchers. We attribute this dissention to different definitions that are given to epileptic spike-like events and the non-standardized EEG datasets. In the same way, determining the appropriate number of decomposition levels also depends on the spike definition and the WT purpose: extraction of features or complementary procedure. Again, the EEG recordings available in the dataset may influence how the signal is decomposed. Depending on the basic rhythm of EEG background activity, presence of noise or movement artifacts, signal sampling rate, data segmentation, and the classification method, a different quantity of sub-bands may be required.

Despite of the fact that the DWT is the approach more frequent in the reviewed works, the DWT has the disadvantage of being a shift-variant transform. To overcome this limitation and restore the time-invariant property, the SWT offers a solution based on non-decimated filter bank (do not down-sampling). Because of its redundant nature, this transform is computationally more complex than the classic DWT [70]. On the other hand, from the investigated literature, the more recent work based in CWT was proposed by Latka [6] in 2003. The CWT does not suffer of either shift-variance or rough resolution. However, the computational cost increases due its highly redundant nature.

The MathWorks[77] MATLAB Toolbox is a well-known suite for digital signal processing and advanced mathematical applications. We noted various authors using MATLAB to compute the WT [41], [43]–[45], [49]–[51], [73]. An interesting question about WT is posed and answered in MathWorks documentation center: "When is Continuous Analysis More Appropriate than Discrete Analysis?" The answer depends on how valued and necessary is a finer resolution to detect the instant when frequency changes occur and how important is saving space. Since CWT demands expensive computational resources and DWT suffers of coarser frequency resolution, WPD overcomes these issues by providing a computationally efficient alternative with sufficient degrees of resolution [71].

3. Other time-frequency decomposition methods

Introduced by Mallat and Zhang [78], the Matching Pursuit(MP) algorithm extends the wavelet decomposition through a dictionary of dilatations and translations of waveform functions, also called *time-frequency atoms*. This adaptive decomposition provides best representation than Fourier and Wavelet transforms, since it is not restricted to a single function or wavelet basis. Sitnikova et al. [79], addressing the sleep spindles and spike-wave detection, chose the *spindle wavelet* mother functions from the EEG signal, instead of a predefined dictionary (i.e. a library of Gabor, Dirac, and Fourier basis waveforms). As observed by Goelz et al. [56], the MP algorithm performs more slowly than the CWT.

Empirical Mode Decomposition (EMD) is a procedure able to decompose adaptively any type of signal into intrinsic mode functions (IMF). Depending on the signal's local maxima and minima points, the method identifies the intrinsic oscillatory modes in the data empirically (upper and lower envelopes, giving a sense of frequency-amplitude modulated). Thus, the signal is recovered from their IMFs and residue. By Hilbert transformation, both energy and frequency components of the data are obtained from each IMF [80]. Dubarry [81] used EMD to detect spikes in EEG signals. Martis et al. [82] designed a feature extraction stage based on EMD, feeding a classifier to separate normal, interictal and ictal sequences. Zhang et al. [83] also based their feature extraction stage on EMD, but for detecting neural spikes (neuronal firing).

D. Mimetic methods

This sub-section summarizes three recent works based on features extracted from the waveform characteristics. Since this approach tries to consider the same morphological information like those observed by a neurophysiologist, it is named mimetic method. Liu et al. [19] defined an epileptic spike consisting of two types of waves: single spike and spike followed by a slow-wave. To form a feature vector, all spike candidates are identified by k-NEO (nonlinear energy operator). Firstly, a candidate peak P is identified from which four other feature points are selected (A, B, Q and R) (see Fig.3). In the next step, 13 features are calculated and categorized by morphological characteristics, including duration, amplitude, slope and area.

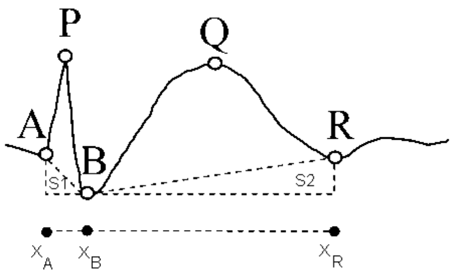

Figure 3 – Feature points of the proposed model. (Liu et al. [19]*)*

Boos et al. [22] took into account the different signals produced by each type of montage (e.g. bipolar or unipolar). Thus, the amplitude peaks of spikes and sharp-waves may have either positive or negative values. They considered a paroxysmal event being a spike followed by a slow-wave. Their approach provides 45 morphological descriptors, categorized into seven groups: amplitude, duration, vertex angle of the peaks, initial region of the epoch, final region of the epoch, statistical indexes and entropy. Those amounts of descriptors were used to distinguish the epileptic spikes from the non-epileptiform events, such as movement artifacts, eye blinks and alpha waves). The feature vector was presented to an ANN classifier.

Ji et al. [23] extracted templates of spikes by using both unipolar and bipolar montages. To each one, a different set of conditions was defined in order to identify the spike part and the slow-wave portion. These conditions consider five morphological descriptors to detect only spikes transients (see Fig. 4). Non-epileptiform events are eliminated, avoiding distorted templates. The templates are clustered and extracted from each focus channel. The multi-channel templates are generated by averaging all spike events.

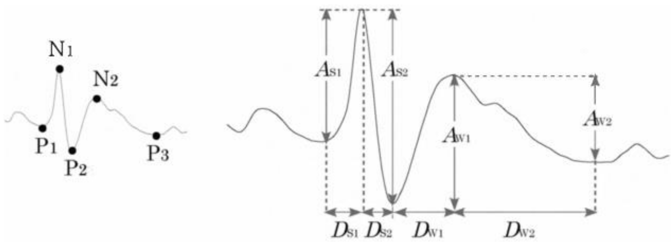

Figure 4 - Features for detecting spikes. Five key points (P1, N1, P2, N2 and P3) and four half-waves (P1N1, N1P2, P2N2 and N2P3) are modeled. For each half-wave, the amplitude and duration are observed. (Ji et al. [23]*)*

The mimetic method is a flexible approach for providing readable and direct information about the signal. Its nature permits the combination of methods for refinement of features, preliminary classification of spike candidates and template extraction. The main obstacle is to graphically characterize the epileptic events, since this requires precise thresholds.

E. Parametric methods

Parametric or model-based techniques rely on modeling the EEG signal by linear or nonlinear estimation methods. Commonly, the estimated signal is expressed as the output of a filter. Hereby, the parameters (also termed coefficients) that best fit the filter's output to the sampled signal under inspection could be used for spike detection, whether by passing it through a threshold or feeding a general classifier. The usual mathematical models are classified as autoregressive (AR), moving-average (MA) and autoregressive moving-average (ARMA). In order to consider the nonstationarity of the EEG signals, adaptive models are required (i.e. the parameters are updated according to the next signal's samples). However, non-adaptive models can be used to fit quasi-stationary segments (i.e. when the signal is partitioned into short intervals) of EEG time series (i.e. the parameters are defined to provide the best representation of the data series)[63]. We briefly describe two works where parametric method was employed.

Oikonomou et al. [84] modeled the EEG using the TVAR model (Time-Varying Auto-Regressive) to enhance spike-like waveforms. Assuming the non-stationarity of the epileptiform events, the time-varying AR parameters were estimated by a Kalman Filter. Their approach diminish the background activity (modelled as a stationary noise) whilst emphasize the spikes.

Acir and Güzeliş [39] applied a nonlinear digital filter (AR model) as a pre-classifier of spikes. The events were categorized into epileptic spikes and trivial non-spikes (like those present in the background activity). In the detection stage, only the spike-like candidates are presented to a Support Vector Machine (SVM) classifier.

F. Classification stage

An automated spike detection system decides whether the data under analysis contains spike events or not. Typically, the classification stages are based on threshold or machine learning (ML) approaches. Threshold is a limit value which is compared to the output of a pre-processing step, including the extracted features, parametric model and template-based methods. In most part of the threshold-based works, an event is classified as a spike when the measured value surpasses the threshold. A threshold may be defined in terms of morphological descriptors (e.g. amplitude and duration [24], [34], [65], [85]), template-matching correlation (e.g. template error measure [16], [26], [30], [31], [42]), parametric modeling [33], [43] and morphological analysis (e.g. WT coefficients, statistic features [6], [18], [45], [49], [56], [57]). By setting the thresholds in an adaptive way may incorporate gain in terms of detection performance, because it compensates the variance of spike amplitude [18].

Similarly, when applying threshold in WT sub-bands, specific values are required to consider the different magnitudes of spikes represented in each level[57].

Machine Learning approaches are suitable for data classification and pattern recognition in feature spaces. For EEG data processing and spike detection tasks, the ML capabilities are valuable, serving either to classify data as spike/non-spike events or to cluster spike-like events. ML algorithms are categorized into supervised learning, when the classifier needs some initial knowledge about the target and produce a discrete output, like (1) “it is a spike event” or (2) “it is not a spike event”; and unsupervised learning, when the classifier does not produce a discrete output, but clusters the data into groups of affinity instead [2].

Boos et al. [22] combined mimetic features and supervised learning, based on neural networks (Feed-forward Multilayer Perceptron with Back-propagation) for detecting spikes in EEG. Given such approach, to perform the training and test steps, the authors applied two compositions of inputs: (1) a non-specific event type, classified only by the presence or absence of spikes and (2) another with specific events, such as sharp waves, spikes, blinks, normal background EEG activity, alpha waves and artifacts. All 45 extracted features were presented as input. The hidden layer size was defined empirically (number of neurons varying from 7 to 11). The output layer was defined with one neuron. Without invalidating the proposed solution, such approach stands out two weaknesses, as also pointed by the authors: (1) the process requires *a priori* knowledge information about the morphology of the signals to be inspected and (2) feature optimization may be required to improve the computation performance. Halford et al. [41], after testing many combinations of different sources of feature extraction with Bayesian- and ANN-based classifiers, observed the best performance when feeding the ANN with the WT features. Gopan et al. [44] used an Adaptive Neuro-Fuzzy Inference System (ANFIS) to classify the features extracted throughout WT and Mean Teager Energy. They justified the use of fuzzy logic to aggregate the uncertainty associated with the medical diagnosis. Inan et al. [86] combined both raw and mimetic parameters with different unsupervised clustering methods, such as fuzzy C-means(FCM) and K-means. By incorporating a pre-classifier stage based on ANN to eliminate the trivial waves, the FCM yielded the best sensitivity while the K-means algorithm produced the best specificity and selectivity.

Support Vector Machine (SVM) is a general classifier also under the supervised learning concept. By training a SVM, both separable and non-separable datasets may be discriminated. In the former case, a linear discriminant function is used (linear hyperplane). In non-separable cases, the dataset may be made separable by using nonlinear discriminant function (non-linear hyperplane) [2]. Different from ANNs, the SVM solution is unique and the computational complexity does not depend on the input size [87]. Acir and Güzeliş [39] proposed the separation of spike and spike like non-spike events after pre-classifying such events in a same group. They designed this post-classifier stage based on SVM. In Lodder et al. [16], the SVM was trained on past classifications leading the template matching to better discriminate between spike and false predictions.

G. Complementary processing

Clearly the feature extraction and the detection/classification stages are complementary to each other and both are essential for automatic spike detection in epileptic EEGs. Nevertheless, in order to obtain the best performance from the detection system, additional processing may be required to address some issues inherent to spike detection problem, such as noise and artifacts rejection, spike enhancement and data reduction.

1. Noise and artifacts rejection

EEG recordings usually have non-epileptiform events uncorrelated with the brain activity that might be misinterpreted by an automatic system of epileptic discharges. In such cases, it is said that EEG is “contaminated” by artifacts, such as electrical line interference, eye blinks, ocular and muscle movements, etc. In terms of performance effects, Hese et al. [31] pointed that some false positives spike recognitions happen due to electrode artifacts while muscle artifacts induced the method of detection to mark correctly the events not selected by the neurophysiologists. In Dingle et al. [65], the use of contextual information was exploited to circumvent the similarities between epileptic events and the artifactual activities. By using spatial context, they focused on remove three types of artifacts: muscle spikes, eye blinks and electrode movement. Ji et al. [67] deal with false positives detections provoked by artifacts by characterizing such events. They defined rules based on morphology and power spectrum to recognize alpha waves, EMG (electromyogram) artifacts, eye blinks and slow waves. In addition, different montages and multi-channel analysis were taken into account to eliminate the false positives.

Due the artifact rejection importance and complexity, some works addressed this subject exclusively. To cite a few, Zhou et al. [88] proposed a WT- and ICA-based approach to remove both EMG and ECG(electrocardiogram) artifacts; Inuso et al. [89] based their work in WT and high order statistics to detect artifactual events. They indicate the designed methodology for being used in pre- and post-processing stages; Mognon et al. [90] conceived an automatic algorithm that detect artifacts in EEG by using Independent Component Analysis (ICA) and additional features (e.g. spatial and temporal contexts).

2. Data reduction & feature optimization

A high-dimensional input data may pose computational obstacles to classifier systems and add complexity to their designs. On the other hand, discarding information may compromise their effectiveness. The first step in reducing the data to be processed is to extract precise features from the original raw data. Such features must retain sufficient information to make possible an accurate classification. However, after extracting a set of features and building a feature vector combining additional information, data optimization may be desirable. For example, some features may either not to contribute to the classifier decision or to be redundant with others. In Sezer et al. [50], the feature vector was extracted from the WT sub-bands and the Principal Component Analysis (PCA) method was applied when necessary to reduce the amount of data. Thereafter, the optimized vectors were presented to the classifier stage. Gopan et al. [44] performed data reduction by selecting one feature among a large set of statistic features calculated on WT coefficients. The optimal feature, the Mean Teager Energy, was given as input to an adaptive neuro-fuzzy classifier.

H. Performance metrics

For completeness, we present a brief review on concepts of evaluation of performance. To guarantee both reliability and robustness to an automated system for recognition of epileptic events in EEG, it is necessary to know what metrics must be considered and how they must be interpreted.

Assuming both spike and non-spike references (also termed as gold-standard) in EEG are properly annotated by experienced neurophysiologists, the following measures have been widely used to compute the performance of an automated spike detection system [11], [91]:

- *True positives* (TP): The number of annotated spikes identified as spikes (hit spikes)
- *False positive* (FP): The number of annotated non-spikes identified as spikes
- *True negatives* (TN): The number of annotated non-spikes detected as non-spikes
- *False negatives* (FN): The number of annotated spikes identified as non-spikes (missed spikes)

The following metrics are usually measured to evaluate the performance of the classifier:

- *Sensitivity*: The capability of the system to detect spikes.

  Sensitivity = TP / (TP + FN)

- *Specificity*: The capability of the system to reject non-spikes.

  Specificity = TN / (TN + FP)

- *Selectivity*: The capability of the system to select precisely true spikes.

  Selectivity = TP / (TP + FP)

- *False positive rate*: The average of false positives occurring in an interval of time (i.e. FP/minute, FP/hour, etc.).
- *Accuracy*: The ratio of correct detections to the total number of detected spike events.

The sensitivity metric is an indicator of how capable the system is to correctly identify the events that match those annotated by the experts. The specificity, selectivity and false positive rate are indicators to estimate how capable the system is to reject the non-spike events. For further details on performance metrics for spike detection systems, refer to [91].

Based on the aforementioned metrics, different approaches of performance evaluation have been proposed. Acir and Güzeliş [39] estimated the classification performance computing both selectivity and sensibility metrics. Halford et al. [41] evaluated their system's performance in terms of sensitivity, specificity and false positives per minute. They remarked that the specificity is an unusual metric in spike detection studies due the difficulty of defining true negative. In Sezer et al. [50], the five ANN-based classifiers were evaluated by applying Receiver-Operator Curve (ROC) analysis. The ROC graph provides a visual evaluation of performance by making a trade-off between sensitivity (vertical axis) and specificity (horizontal axis). The Area Under the Curve (AUC) value gives the classification test's discrimination capability. To illustrate the lack of standardized definitions, in Xu et al. [47], the sensitivity and selectivity metrics (as defined above), were termed as *detection rate* and *accuracy*, respectively.

I. Dataset

In automated epileptic spike detection context, a dataset corresponds to a collection of digitized EEG data sample, from either human or rats EEG recordings, typically. In some studies, synthetic signals were also used [34], [43]. Especially in supervised learning- (i.e. when the classifier stage requires a training step) and template-based systems, a large dataset plays a fundamental role to ensure a good performance in terms of spike detection/classification. Even in solutions that neither require human intervention nor training stage, a substantial and varied amount of samples is desired for a proper evaluation. An adequate EEG dataset not only requires a big population of patients but also a sufficient quantity of diversified patterns of epileptiform and non-epileptiform events under different contexts, such as wakefulness and sleep states. For instance, Gotman and Wang [92] developed methods of spike detection to act on five distinct states (active wakefulness, quite wakefulness, desynchronized EEG, phasic EEG and slow EEG) .

Despite the fact of a considerable part of the reviewed studies used EEG recordings captured with the standard 10-20 system electrode placement [3], the heterogeneity of the data arises with different data sampling rates (256Hz [29],[41]; 200Hz [40]; 173.6Hz [42]; 128Hz [47]; 100Hz [53]), different number of electrode channels (32 [30],[53]; 22 [47]; 21 [51]; 16 [40]; 8 [54]) and divergent definitions of spike given by the neurophysiologists, not to mention the disparities among patients population, registers duration and quantity of marked spike events. Such characteristics imply difficulties to compare the reviewed works in terms of detection performance. Public repositories of data sample used by some authors are available in [93]–[95].

J. Literature reviews

Table 3 provides 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 3 - Literature reviews on automated EEG analysis

Work	Year	Review focus
Acharya et al. [96]	2013	Feature extraction methods
Tzallas et al. [10]	2012	Spike and seizure detection methods
Nasehi and Pourghassem [12]	2012	Seizure detection algorithms, dataset and performance evaluation measures
Song [97]	2011	Seizure detection, feature extraction and classification models
Halford [98]	2009	Spike detection, dataset comparison, performance evaluation
Casson et al. [91]	2009	Performance metrics
Tamil et al. [68]	2008	Feature extraction and classification models
Pang et al. [11]	2003	Comparison of algorithms for spike detection
Wilson and Emerson [14]	2002	Spike detection and accuracy comparison

IV. Final remarks

We emphasized the approach on Wavelet Transforms due its evidenced efficiency extracting features from nonstationary 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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