Review: A Survey of Performance and Techniques for Automatic Epilepsy Detection

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Abstract

Epilepsy is a chronic neurological disorder of the brain that affects around 50 million people worldwide. The early detection of epileptic seizures using electroencephalogram (EEG) signals is a useful tool for several applications in epilepsy diagnosis. Many techniques have been developed for unscrambling the underlying features of seizures present in EEGs. This article reviews the seizure detection algorithms developed in the last decade. In general terms, techniques based on the wavelet transform, entropy, tensors, empirical mode decomposition, chaos theory, and dynamic analysis are surveyed in the field of epilepsy detection. A performance comparison of the reviewed algorithms is also conducted. The needs for a reliable practical implementation are highlighted and some future prospectives in the area are given. Epilepsy detection research is oriented to develop non-invasive and precise methods to allow precise and quick diagnoses. Finally, the lack of standardization of the methods in the epileptic seizure detection field is an emerging problem that has to be solved to allow homogenous comparisons of detector performance.

Keywords: Epilepsy; Seizure detection algorithm; Performance

1. Introduction

Epilepsy is a chronic neurological disorder of the brain that affects around 50 million people of all ages in every country in the world. According to the World Health Organization (WHO), epilepsy is characterized by recurrent seizures, which are physical reactions to sudden, usually brief, excessive electrical discharges in a group of brain cells [1]. In the context of epilepsy monitoring, two types of seizure have to be considered, namely behavioral and electrographic. A behavioral seizure is defined as the clinical manifestations of epilepsy, as perceived by the patient, seen by an observer, or recorded on video. A electrographic (or electroencephalographic (EEG)) seizure is defined as an abnormal paroxysmal EEG pattern. In many cases, there is dissociation between behavior and EEG signals [2].

Automatic EEG seizure detection, quantification, and recognition have been areas of concern and research within the clinical, physics, and engineering communities since the 1970s. In clinics, for patients with medically intractable partial epilepsies, time-consuming video EEG monitoring of spontaneous seizures is often necessary. Visual analysis of interictal EEG is, however, time-intensive so the automated detection of seizures in long-term EEG records is very useful, as it reduces the information that a specialist has to analyze in order to make a diagnosis about the type of epilepsy or to determine the epileptic source. The automated detection of the time onset and quantification of an EEG epileptic seizure is also useful in drug delivery systems or neurostimulation devices [3-6]. Another important line of research is regarding seizure prediction based on precursors of impending epileptic seizures. There is evidence that seizures are preceded by characteristic changes in the EEG that are detectable minutes before seizure onset [7]. This would allow the dynamic mechanisms underlying the disorder to be elucidated, as well as enable implantable devices to intervene in time to treat epilepsy [8-10]. This is a complex area that has to be treated independently.

Some examples are given below to better explain the seizure detection problem. Figures 1(a) and (b) show 100-second records for 4 channels of a scalp EEG, with the preictal, ictal and postictal states shown. In Fig. 1(a), these three states are easy to distinguish by visual inspection whereas in Fig. 1(b), the epileptic seizure can go unnoticed in a first or quick examination by a neurologist. There is thus a need to find features such as amplitude, duration, and frequency that help to distinguish an epileptic seizure from the background. However, visually inspecting changes in these features and wave morphology is difficult, subjective, and time-consuming. The development of automatic tools for seizure detection from EEG records is thus desirable.

This paper outlines the processing techniques and classifiers used for epilepsy detection. A performance comparison of the reviewed seizure detection algorithms is also

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conducted. An overview of the blocks of a seizure detection system is given.

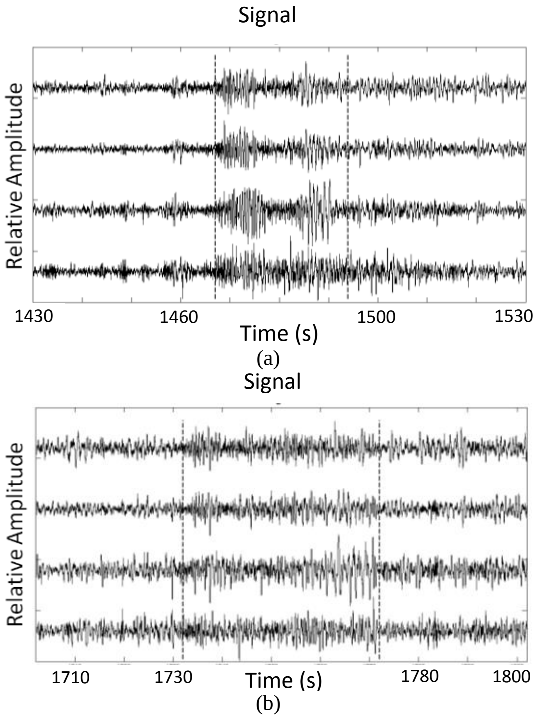

Figure 1. Examples of two epileptic seizures from CHB-MIT Scalp EEG database [92]. Four channels of EEG record of epileptic seizure of Patient 1, segments (a) 4 and (b) 15. In (a), preictal, ictal, and postictal states are easy to distinguish by visual inspection, whereas in (b), visual differences between these three states are difficult to discern. Black lines indicate the time boundaries of a seizure annotated by an expert.

2. Detection system

A seizure detection system can be divided into three stages: data acquisition and preprocessing, processing and feature extraction, and decision-making. The following sections describe these blocks.

3. Preprocessing

In biomedical signal processing, it is crucial to determine the noise and artifacts present in the raw signals so that their influence in the feature extraction stage can be minimized. EEG recordings have a wide variety of artifacts, some having a technical origin and others having a physiological origin [11]. The preprocessing stage attempts to eliminate these artifacts without losing relevant information.

Noise of technical origin depends on the acquisition settings, which are related to the type of EEG (scalp or intracranial), including gain (vertical resolution), cut-off frequencies of high-pass and low-pass filters, characteristics of the notch filter, and sampling rate [12].

Physiological artifacts include those caused by ocular (electroculogram: EOG) and muscle (electromyogram: EMG) activity as well as heart rate (electrocardiogram: ECG), which overlap with the frequencies of interest in EEG seizure detection. Several methods have been proposed to diminish such interference, such as conventional filtering and artifact cancellation using combined reference signals [11].

In [13], intracranial EEG (iEEG) signals were band-pass-filtered between 0.5 and 100 Hz to only allow the frequencies of interest and a notch filter was used to remove 50-Hz power line noise. Saturation and movement artifacts were identified. Segments for which the derivative of the iEEG signal was zero were marked as having saturation artifacts. Movement artifacts were discarded using a threshold; iEEG segments containing a signal with amplitude of larger than 1.5 mV were considered as having movement artifacts. In [14], a wavelet filter that requires the frequency content to be limited to the 0-60 Hz band is used, so the EEG is band-limited to the desired band by convolving with a low-pass finite impulse response (FIR) filter.

Some techniques, such as independent component analysis (ICA), are specifically used for artifact cancellation. ICA identifies sources, in this case artifacts present in the EEG signal, based on blind source separation (BSS) and separates them from the EEG based on their statistical independence [12,15]. This subject is detailed in Section 4.5.

Another technique for artifact cancellation is adaptive filtering, which uses a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. The accuracy of the method has been evaluated using simulated data [16]. The method has been used to remove ocular artifacts from EEG [17]. Mourad *et al*. used a blocking matrix that adaptively rejects high-amplitude artifacts present in simulated EEG data [18]. A cascade of three adaptive filters based on a least mean squares algorithm has been proposed to remove the common noise components present in the EEG signal [19]. The first filter in the cascade eliminates power-line interference, the second removes the QRS complexes of the ECG signal, and the last one cancels EOG artifacts. Each stage uses an FIR filter, which adjusts its coefficients to produce an output similar to the artifacts present in the EEG. Finally, the output of the cascade gives an EEG signal without artifacts [19].

To remove artifacts from EEG signals, multi-way analysis decomposes EEG data into space-time-frequency components. Multi-channel EEG data has been constructed as a third-order tensor, an epilepsy feature tensor, with modes: time samples × frequency × electrodes [20]. This allows the spectral, spatial, and temporal signatures of an artifact to be found to define it using parallel factor (PARAFAC) analysis. Then, through multilinear subspace analysis, artifacts such as eye movements are removed so that the remaining data does not contain any activity correlated with the artifact [20]. More detailed definitions about tensors are given in Section 4.6.

The preprocessing block also normalizes the signal to make the data comparable with those recorded by another acquisition system or from a different patient. An example of this is putting all the data in a given amplitude range, allowing the signals to be compared directly [21].

4. Processing and feature extraction

In an automated seizure detection system, the distinctiveness of the EEG signals before, during, and after a seizure has to be determined and evaluated. Several features have been identified to better describe the behavior of seizures. These may represent the static behavior of the signals in both time and space or the dynamic properties, such as chaoticity and non-linearity [12].

In this section, the terms processing technique and feature extraction are used interchangeably for some techniques due to their close relation; for example, wavelet features make reference to the wavelet transform (WT) of the signal. Since the EEG signal has non-linear and non-stationary characteristics, linear processing techniques have to be applied to a windowed version of the signal, where it is assumed to be linear and stationary. Even though the technique to be applied is suitable for this kind of signal, windowing is always used because the events to be detected are transitions between non-seizure, pre-seizure, and seizure states [21]. Some studies have analyzed single-channel EEG signals [22,23] whereas others have used multi-channel analysis to evaluate synchronization between EEG channels [24].

Selecting features that best describe the behavior of EEG signals is important for seizure detection and classifier performance. Many types of features and processing techniques have been proposed, including those based on time-domain [25,26], frequency-domain [19,33,34,13,27,28], or time-frequency analysis [31], energy distribution in the time-frequency plane [29-32], wavelet features [33-35], and chaotic features such us entropy [23,36]. Another technique is multi-way analysis, which uses feature tensors to identify seizures [20,37-40].

Most detectors use a combination of two or more techniques and test a given set of features with more than one classifier [41-43].

4.1 Time-domain analysis

EEG signals are a function of time so directly estimated features are called time domain analysis. Often used features include amplitude, regularity, and synchronicity, which increase during epileptic events.

Amplitude refers to the signal instantaneous energy. Its square is the signal power, which emphasizes changes more than energy but is consequently more affected by noise. This feature was used by Minasayan *et al*. [26], who combined it with other parameters to construct an input vector to an artificial neural network (ANN) classifier. Figure 2 shows an example of EEG signal instantaneous energy. Notice the remarkable increase of energy during the epileptic seizure (bounded by black lines).

Regularity is obtained using an auto-correlation function, which measures the similarity of a signal with itself. Windowing analysis gives an idea of periodicity, which can be used to identify how regular a signal is [21].

Synchronicity gives an idea of how similar signals are to each other or what events occur at the same time. Several methods, such as cross-correlation and mean phase coherence, exit for measuring various types of synchronicity [25].

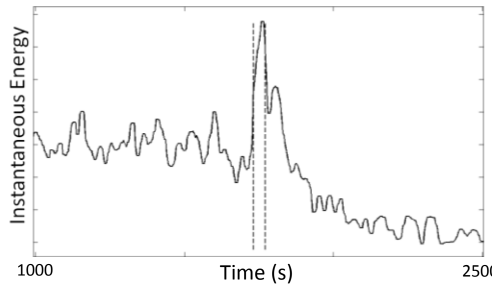

Figure 2. Signal instantaneous energy, showing an increase during a seizure. Black lines indicate the time boundaries of a seizure annotated by an expert.

Usually, time features are used in seizure detection algorithms. For example, relative average amplitude, relative average duration, and the coefficient of variation of amplitude are implemented in the commercial seizure detection algorithm Monitor [44,45]. Monitor is used as a gold standard even though its detection accuracy is under 80%. Therefore, researchers, including Saab and Gotman [46] and Aarabi [13], have improved these parameters.

Acharya *et al*. proposed higher order spectra (HOS) features (specifically cumulants) from normal, interictal, and epileptic EEG segments for time series analysis, obtaining a high detection accuracy of 98.5% [47]. Other researchers reported achieving a 93.11% classification accuracy with HOS-based features [48,49]. Other works combined HOS with principal component analysis (PCA), achieving detection accuracies of over 95% [50].

4.2 Frequency-domain analysis

During an epileptic seizure, there is usually a change in the frequency components of the EEG signal, as shown in Fig. 1(a). This change needs to be quantified to provide useful information. To extract frequency features, the signal has to be described in terms of its frequency components, which is done using the Fourier transform. Frequency features can be used to isolate brain activity at different frequencies. In general, power spectral density (PSD) is calculated and then relevant features are extracted [21]. Figure 3 shows the PSD of 3 EEG segments of a given patient. Peaks in the bands 0.5-5 Hz and 10-15 Hz are present only during a seizure (grey curves versus black curves (no seizure)).

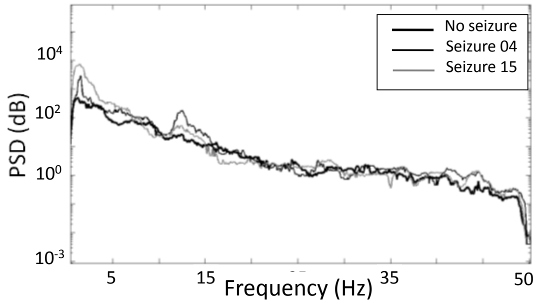

Figure 3. PSD of a seizure-free segment and two segments with seizures.

Some common spectral features are average band frequency, maximum power [51], central, mean, and peak frequencies [52], and dominant frequency [13]. In general, studies combine frequency analysis with time and other features for more accurate detection due to the complexity of detecting seizures.

4.3 Time-frequency analysis

Even though time and frequency analyses are widely used in signal processing, they have well known disadvantages when applied to signals such as EEG. Time-domain analysis can be used to assess the exact location of events but it cannot distinguish which frequencies are involved in those events. Frequency-domain analysis differentiates the frequencies present in a signal but not the time moment of their occurrence. Due to these limitations, time-frequency analysis techniques have been developed. A classical method, such as spectrography, was used by Gabor *et al*. [29] and Gabor [30] to implement their commercial detector CNet. Other approaches include Gabor atoms, Wigner-Ville distribution (WVD) [53], and wavelet analysis, which is the most widely used for EEG.

4.3.1 Wavelet transform

The WT is a multiresolution decomposition of a signal into sub-band signals containing activity at different time scales achieved by passing the signal through an iterated filterbank structure [53]. This versatile signal processing tool captures transient features and localizes them in both time and frequency domain accurately. This transform analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a coarse approximation and detailed information [54-56].

For epileptic seizure detection, many researchers have applied the WT. Shoeb *et al*. [57] used wavelet decomposition to construct a feature vector that captures the morphology and spatial distribution of an EEG epoch. Meier *et al*. [25] combined wavelet and time features as input for a support vector machine (SVM) classifier. Abibullaev *et al*. [35] tested various wavelet functions (db2, db5 and bior1.3, bior1.5) to detect and extract ictal epileptic seizure spikes. The commercial seizure detection algorithm Saab is based on the computation of the relative amplitude and the coefficient of variation of wavelet coefficients and a pure probabilistic classification with Bayesian formulation [46]. Other studies that use the WT are summarized in Table 1.

Daubechies 2, 4, and 8 wavelet functions are the most widely used for seizure detection. The sub-band in which the characteristics of a particular seizure can be best distinguished depends on the sampling rate of the original signal. Figure 4 shows a scalp EEG signal with a sampling frequency of 256 Hz and its 6-level wavelet decomposition obtained with Daubechies 4. The first levels of decomposition contain the highest frequency components of the signal while the last scales show the low-frequency content of the signal. Note that the sub-bands D5 and D6 have the highest increases in energy levels during the seizure bounded by black lines. In general terms, sub-bands of higher frequencies capture high-frequency artifacts similar to those resulting from muscular contractions while those detail signal ranging from 0.5 to 30 Hz capture seizure onsets [45,57].

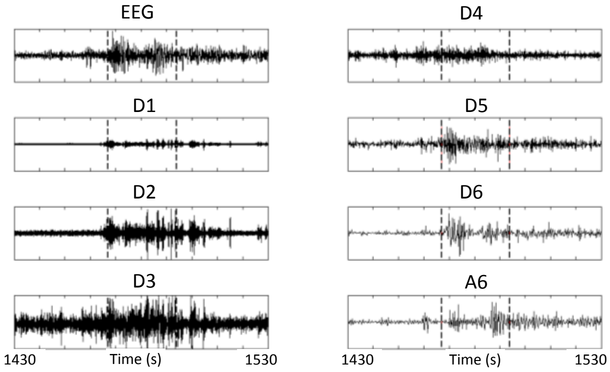

Figure 4. Daubechies 4 decomposition of a seizure EEG (scalp) signal with 6 levels of details (D1… D6). The sub-band ranges in Hz are approximately: D1 = 64-128; D2 = 32-64; D3 = 16-32; D4 = 8-16; D5 = 4-8; D6 = 0-4; A6 = 0-4. Black lines indicate the time boundaries of a seizure annotated by an expert.

4.3.2 Wigner-Ville distribution

The WVD is one of the most studied and best understood time-frequency distributions [53]. This particular distribution has very good resolution in both the time and frequency domains, and has interesting time and frequency support properties [15]. Tzallas *et al*. [32] applied the WVD to selected segments of EEG signals and extracted several features for each segment that represent the energy distribution in the time-frequency plane. The calculated features are fed into a feed-forward ANN. To reduce the dimensionality of the input patterns, PCA is also employed.

Figure 5 (lower panel) shows the WVD of the EEG seizure segment of the upper panel; note the increase of amplitude (brighter colors) during the seizure.

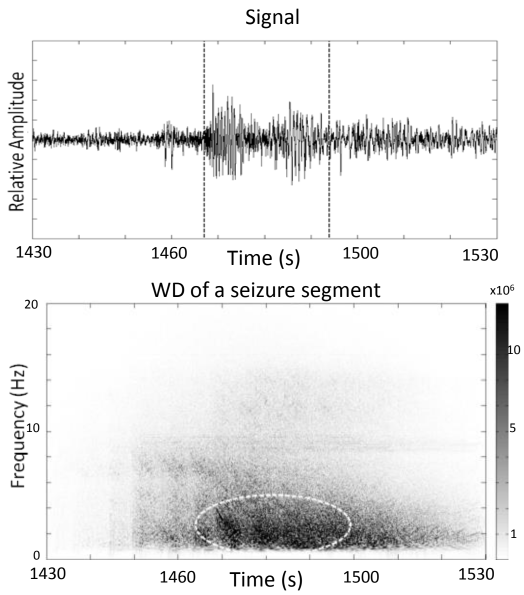

Figure 5. Wigner-Ville Distribution (lower panel) of EEG seizure segment of the upper panel. The white ellipse bounds the region of the time-frequency plane that represents the seizure activity.

Table 1. List of reviewed publications, summary of classifiers, and database characteristics used by researchers.

Reference	Processing techniques	Classifier type	Database: Center/Hospital - EEG Type	Patients
Monitor Algorithm Gotman, (1982; 1990)	Time analysis	Thresholds	Canada - SEEG	Pediatrics
CNet algorithm Gabor *et al*. (1996) and Gabor (1998)	TF analysis/2DFFT	SOM/ANN	University of California, Davis Medical Center - SEEG	NR
Niederhauser, *et al*. (2003)	TF analysis/Maximum excursion of JSPECT	Thresholds	Emory Epilepsy Monitoring – IEEG	NR
Reveal Algorithm Wilson *et al*. (2004)	MP (Gabor Atoms)	ANN	Columbia P. Hospital/Universities of Pittsburgh and California, Davis Medical Center - SEEG	Pediatrics/Adults
Shoeb *et al*. (2004)	Wavelet	SVM	Hospital NR - SEEG	Pediatrics
Kannathal *et al*. (2005)	Shannon spectral entropy/ Renyi entropy / Kolmogorov entropy/ ApEn	ANFIS	Andrzejak – IEEG/SEEG	Adults
Güler and Ü beyli (2005)	Wavelet	ANFIS	Andrzejak – IEEG/SEEG	Adults
Subasi (2005)	Wavelet	ANN	Hospital NR - SEEG	Pediatrics/Adults
Saab Algorithm Saab and Gotman (2005)	Wavelet	Bayesian formulation	Montreal Neurological Institute and Hospital, Canada - SEEG	NR
Grewal and Gotman (2005) [93]	Time Analysis	Bayesian formulation	Montreal Neurological Institute and Hospital -IEEG	NR
Gardner *et al*. (2006)	Energy-based statistics	SVM	Hospital NR- IEEG	Adults
Subasi (2006)	Wavelet	DFNN	Hospital NR - SEEG	Pediatrics/Adults
Aarabi *et al*. (2006)	Time analysis/ Frequency analysis/ Wavelet/ Auto Regressive Coefficients / Cepstral analysis	ANN	North Hospital of Amiens, France - SEEG	Newborns
Subasi (2007)	Wavelet	ANN	Andrzejak – IEEG/SEEG	Adults
Adeli (2007)	Wavelet/ CD/ LLE	Confidence Interval	Andrzejak – IEEG/SEEG	Adults
Polat and Günes (2007)	Frequency analysis	Decision tree	Andrzejak – IEEG/SEEG	Adults
Tzallas *et al*. (2007)	TF analysis (PWVD)/Energy distribution in TF plane	ANN	Andrzejak – IEEG/SEEG	Adults
Chan *et al*. (2008)	Frequency analysis	SVM/ Clustering and Regression Model	RNS™ System, NeuroPace, Inc., Mountain View, CA - IEEG (6 patients)	Adults
Meier *et al*. (2008)	Wavelet/ Time analysis	SVM	University Hospital Freiburg, Germany - SEEG	Adults
Schad *et al*. (2008)	Time analysis	Thresholds	FSPEEG – IEEG (6 patients)	Adults
Deburchgraeve *et al*. (2008)	NLEO Wavelet	Correlation Analysis Autocorrelation Analysis	Sophia Children’s Hospital, Rotterdam, The Netherlands - SEEG	Newborns
Gardner *et al*. (2008)	Short-time energy	Thresholds / Kolmogorov-Smirnov test	The Children's Hospital of Philadelphia – IEEG (2 patients)	Pediatrics/Adults
Aarabi (2009)	Entropy/Frequency and Time analysis	Fuzzy Rules/ANN	FSPEEG - IEEG	Adults
Mitra *et al*. (2009)	Frequency analysis /Wavelet/Spatio-temporal clustering	ANN/ Context-based Rules	NICU of Texas Children’s Hospital - SEEG	Newborn
Ü beyli (2009)	Eigenvectors in Frequency domain	MLPNN/RNN	Andrzejak – IEEG/SEEG	Adults
Guo *et al*. (2010)	Wavelet	ANN	Andrzejak – IEEG/SEEG	Adults
Minasyan *et al*. (2010)	Frequency and Time analysis /Wavelet /Complexity measures	RNN	Medical centers from T. Jefferson, Dartmouth, Virginia, UCLA and Michigan Universities - SEEG	Adults
Abibullaev *et al*. (2010)	Wavelet	ANN	Dongsan Medical Center, South Korea - SEEG	Adults
Zandi *et al*. (2010)	Wavelet	Cumulative thresholds	Vancouver General Hospital (VGH) - SEEG	Adults
Marsh *et al*. (2010)	Time analysis	Thresholds	The Children's Hospital of Philadelphia – IEEG	NR
Temko *et al*.(2011a)	Frequency / Time analysis	SVM	NICU of Cork University Maternity Hospital, Ireland	Newborns
Orosco *et al*. (2011)	EMD/IMF’s Energy EMD/IMF’s Frequency / Time analysis	Thresholds LDA	FSPEEG - IEEG	Adults
Yuan *et al*. (2011)	ApEn/ Hurst exponent/ DFA	ANN/SVM	Andrzejak – IEEG/SEEG	Adults
Oweis and Abdulhay (2011)	MEMD/ EMD	t-test/Euclidean clustering	Andrzejak – IEEG/SEEG	Adults
Orhan *et al*. (2011)	Wavelet	*k*-means clustering/PD/ANN	Andrzejak – IEEG/SEEG	Adults
Raghunathan *et al*.(2011)	Wavelet- Two linear time-based features	Simultaneous increase of features	FSPEEG – IEEG (5 patients)	Adults

4.3.3 EMD

Empirical mode decomposition (EMD) [58] is an adaptive method introduced to analyze non-linear and non-stationary signals. It consists in a local and fully data-driven separation of a signal in fast and slow oscillations. The aim of the EMD is to decompose the signal into a sum of intrinsic mode functions (IMFs). An IMF is defined as a function that satisfies two conditions: (1) in the entire signal, the number of extrema and the number of zero crossings must be equal or differ at most by one; (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero (or close to zero).

EMD has been used for epileptic seizure detection. Oweis and Abdulhay [59] decomposed the EEG signal in 10 IMFs and then extracted their local amplitude and frequency. Based on this local information, weighted frequencies are calculated and a comparison between ictal and seizure-free determinant intrinsic functions is performed. Methods such as the t-test and Euclidean clustering can be used for comparison. Orosco *et al*. [52] developed two detectors based on the EMD of multi-channel EEG signals containing segments with and without seizures. The first detector computes the energy of the IMFs and a seizure is detected when this energy go up a threshold of amplitude and last more than 30s. The second detector extracts time and frequency features from IMFs and then performs linear discriminant analysis (LDA) for classification into seizure and no seizure states. In [60], the instantaneous area measured from the trace of the windowed analytic IMFs of EEG signals was used for the rules-based detection of focal temporal lobe epilepsy. The method was tested on intracranial EEG signals, with good detection accuracy of focal temporal lobe epilepsy found.

Figure 6 shows a scalp EEG seizure record and its 6 IMFs. It is notable how in IMF4, 5 and 6 particular oscillations appear during the seizure time (black lines). Consequently, these functions can be used for seizure detection. The modes in which these distinctive frequencies appear vary because the EMD depends directly on the frequency content of the signal. This aspect makes the technique dissimilar from the WT.

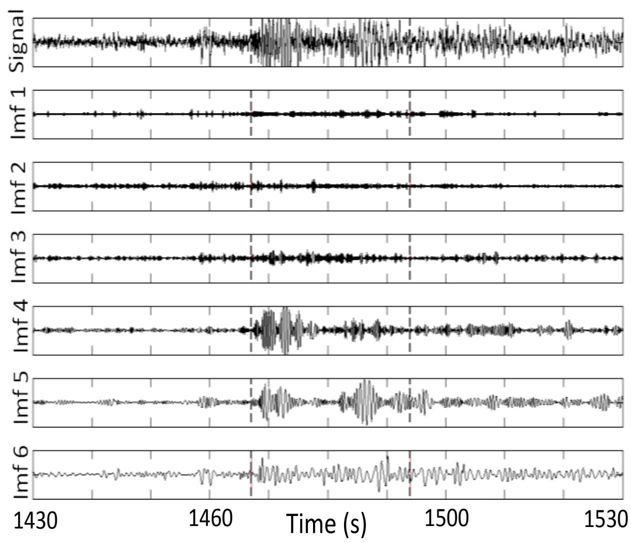

Figure 6. EEG scalp record and its 6 IMFs during an epileptic seizure.

4.3.4 Matching pursuits

Matching pursuit (MP) is an iterative algorithm that finds a suboptimal solution to the problem of an optimal representation of a signal in a redundant dictionary. MP decomposes the analyzed signal into a weighted sum of known functions which represent the oscillations and transients present in the signal [61]. These functions are known as Gabor atoms, and a set of them constitutes the Gabor dictionary. The MP algorithm finds the best single atom in each step and then subtracts the contribution of this atom from the data. This process continues for a fixed number of iterations or until the error of the residual data reaches an acceptable size. The use of Gabor atoms offers precise time-frequency resolution.

This technique is implemented in the commercial seizure detection algorithm Reveal, developed by Wilson *et al*. in 2004 [68]. A wavelet package is used as atoms instead of Gabor atoms in order to speed up the computation time. Connected-object clustering and seizure detection are performed using a set of ANN rules [62].

4.4 Chaos and dynamic analysis

EEG signals are non-linear and non-stationary, and can be considered chaotic, and thus exhibit dynamic behavior. These signals can be characterized using tools that evaluate the state of chaos of a dynamic system. Entropies and Lyapunov exponents are effective tools for such evaluation [15]. Acharya *et al*. used recurrence plots of EEG signals to extract recurrence quantification analysis parameters to classify EEG signals into normal, ictal, and interictal classes. Good classification accuracy was found in differentiating the three types of EEG segment [63]. Adeli and Ghosh-Dastidar proposed an integrated approach that uses chaos theory and wavelets for EEG analysis [43].

4.4.1 Entropy

In general, entropies are measures that give an idea of how disorderly a system is. From the information theory perspective, the concept of entropy is described as the amount of information stored in a general probability distribution. Higher entropy represents higher uncertainty and a more chaotic system. Recently, a number of entropy estimators have been applied to quantify the complexity of signals [64]. Shannon spectral entropy, Renyi's entropy, Kolmogorov-Sinai entropy, and approximate entropy (ApEn) [65] are the most commonly used entropies.

Kannathal *et al*. [36] applied various entropy estimators to EEG data from normal and epileptic subjects to compare their ability to distinguish normal and epileptic EEG data, they achieved a classification accuracy of about 90%. Aarabi [52] integrated ApEn and time and spectral features, extracted from IEEG segments, into a fuzzy rules-based system for seizure detection. Yuan *et al*. [23] used ApEn and Hurst-exponent-like features as inputs to classifiers based on ANN and SVM.

4.4.2 Lyapunov exponents

Lyapunov exponents mathematically describe the deterministic structure of a system. These exponents are statistics that quantify how much a system changes when a small perturbation is introduced [21]. Smaller Lyapunow exponents indicate a more deterministic system.

Adeli *et al*. [14] conducted a chaos analysis based on the wavelet decomposition of EEG signals of healthy subjects, epileptic subjects during a seizure-free interval, and epileptic subjects during a seizure. The non-linear dynamic of the original EEGs is quantified in the form of the correlation dimension (CD) and the largest Lyapunov exponent (LLE), representing system chaoticity, of the different sub-bands of the EEGs for the detection of epileptic seizures. The effectiveness of these indexes was investigated based on statistical significance of their differences between the EEG sub-bands. It was found that the LLE differentiates between the three groups in the lower frequency alpha sub-band [14]. Moreover, Adeli and Ghosh-Dastidar [43] presented a complete strategy for seizure detection. A wavelet-chaos methodology was presented for analysis of EEGs and EEG sub-bands for the detection of seizures and epilepsy. The method consists of three stages: I) wavelet analysis, II) preliminary chaos analysis, and II) final chaos analysis. They use, as before, the estimators of CD and LLE. They also evaluated 4 types of classifier. The method was applied to EEG signals from (a) healthy subjects, (b) epileptic subjects during a seizure-free interval (interictal EEG), and (c) epileptic subjects during a seizure (ictal EEG). The classification accuracy was higher than 95% [43].

4.5 Independent component analysis

ICA belongs to a class of BSS methods for separating data into underlying informational components. ICA separates a set of signals into a corresponding set of statistically independent component signals or source signals. This analysis is based on the physically realistic assumption that if the signals in a set are from different physical processes, then these signals are statistically independent. For further reading about ICA and the mathematical formulation, refer to [66].

De Vos *et al*. [67] developed algorithms that decompose the EEG using ICA into its underlying sources. The aim is to remove artifacts from ECG spikes, blood vessel pulsation, and respiration using BSS. Then, the EEG is reconstructed without the corrupting sources, leading to a clean EEG. The impact of artifact removal was evaluated by comparing the performance of a previously developed seizure detector [24] before and after artifact removal. They obtained a high sensitivity combined with a good PPV and much lower false positive rate than previously published algorithms.

Other researchers proposed automatic methods for artifact removal from epileptic EEG signals that combine BSS and wavelet denoising (WD). The goal is to find the optimal combination of BSS, classification, and WD. These works attempt to find the optimal order that the techniques have to be applied in order to not miss relevant information about seizures. They concluded that the first processing step should be BSS (to identify artifact sources) and then WD (to eliminate additive noise) [68,69].

4.6 Tensors

The most frequent computational models used to reconstruct complex systems, such us epileptic seizure behavior, are bimodal, i.e., those that only consider row-column relationships. In contrast, multi-way modeling techniques (tensor models) can analyze multimodal data, which capture much more information about complex behaviors. In particular, tensors can be very powerful tools for modeling dynamic systems. Tensors are multidimensional arrays (also called n-dimensional cubes) ideally suited for the multi-way analysis of multimodal data [70].

Tensor models have been applied to epilepsy detection. Acar *et al*. constructed multi-channel EEG data as a third order tensor (epilepsy feature tensor) with modes time samples × frequency × electrodes using a PARAFAC model and then employed these components to define a seizure. Seizure origins are localized based on the spatial signature of a seizure extracted from a PARAFAC model. The preliminary results indicated that the features of an artifact and a seizure can be extracted using multi-way analysis of multi-channel EEG data arranged as a three-way tensor. Nevertheless, there exist many research directions for improving and generalizing the results with their proposed method [20,37,38]. De Vos *et al*. proposed a three-way array tensor of EEG signals with dimensions (channels × time × scales) and developed a method using PARAFAC or canonical decomposition (CP) in order to detect the onset [39] and the source localization [40] of epileptic seizures. CP can be considered as the higher-order variant of factor analysis. It uniquely decomposes EEG into a series of distinct 'atoms', which represent in an ideal situation distinct brain sources. The CP method was tested on simulated data and proved to be a fast method for delineating the ictal onset zone and to be more sensitive than visual interpretation of ictal EEGs.

4.7 Feature selection

Generally, selecting the best features for classification is critical for classifier performance. For example, if two or more features are correlated, they represent redundant information that may confuse the classifier.

Some basic statistics, such as average power, mean, entropy, and standard deviation of the wavelet coefficients in each sub-band, are used to reduce the dimensionality of feature vectors [33,71-73]. One-way analysis of variance (ANOVA) is a collection of statistical models used to analyze the differences between group means in which the observed variance in a particular variable is partitioned into components attributable to different sources of variation [74]. The Mann-Whitney Test is used like a non-parametric test that compares the mean values of two different data populations combined with the Lambda of Wilks (LW) criterion [52]. LW measures the ratio between within-group variability and total variability, and is a direct measure of the importance of the variables. Mihandoost *et al*. used the Markov random field (MRF) to select the best features. Class separability is utilized as a criterion to select suitable features; that is, the between-class distance is maximized whereas the within-class distance is minimized. In this method, non-linear mapping from the input space to the output space is utilized [75].

Feature reduction techniques specific to the used processing method have been proposed, such as those applied for extracting the correct number of components in a multilinear model like residual analysis, visual appearance of loadings, the number of iterations of the algorithm, core consistency, etc. In [20], the core consistency is used for finding the number of components of a PARAFAC model that best describe a seizure signature. Mutual information, a measure of linear and non-linear interdependence between features [76], is also used as a feature selection criterion. Minasayan *et al*. utilized this technique to implement an algorithm for automatic feature selection to built a mutual information feature selector that evaluates mutual information between individual features and outputs (class labels), and selects those features that have maximum mutual information with outputs and are not redundant [26]. The Euclidean distance was used by Orhan *et al*. as a dissimilarity measure in a *k*-means algorithm computed according to the distribution of wavelet coefficients [77].

5. Classification algorithms

Once the previously described stages of the detection system have been carried out and assuming that the features extracted are suitable for distinguishing between non-seizure and seizure EEG states, the information is used to decide the class to which the features belong to. A decision-making stage and classification of the data in the feature space are thus required. This step is a global process that encapsulates a strategy for determining what features to select, how to combine them in order to optimize the system performance.

The objective of classification is to describe a boundary between the classes and to label them based on their measured features. The classifier can be as simple as fixing a threshold for features or more sophisticated, such as machine learning algorithms. In a multidimensional feature space, this boundary is converted into a separating hyperplane. The purpose is to find the hyperplane that has the maximum distance from all the classes.

Several clustering and classification techniques have been developed. Among them, association rules, ANNs, LDA, hidden Markov modeling (HMM), *k*-means clustering, fuzzy logic, and SVMs have been applied to epileptic seizure detection. The mathematical foundations of these techniques have been developed and are well explained in the literature. Therefore, only brief descriptions and seizure detection applications are given below.

Association rules are used to inspect the feature set and establish simple relationships between the features. Thresholds are often used to make decisions. Gotman proposed the Monitor algorithm [44,45], which uses the thresholding of time features (amplitude, duration, and coefficient of variation of amplitude) to detect seizures. Schad *et al*. [78] propose a threshold of local slopes in EEG signals to make the seizures detections. Niederhauser *et al*. [31] employed a threshold for time frequency features. Gardner *et al*. [79] also did so but with a short time energy. Mitra *et al*. [41] established a set of rules (different from thresholds) for artifact rejection, followed by rules for assessing overall seizure quality. Other researchers also used association rules for seizure detection [52,80,81].

When the relationships between features are complex, automated methods for finding them are required. Techniques such as LDA [52], fuzzy logic [33,36,55], and *k*-means clustering [83] are used for epilepsy detection (see Table 1). The most commonly used classifiers in the last decade are based on ANNs, following by SVMs.

ANNs are a mathematical analogy of the low-level functions of biological neurons. In an ANN, knowledge about the problem is distributed in each functional unit (neuron) and connection weights of links between neurons. The neural network has to be trained to produce the desired mapping. In the training stage, feature vectors are used as inputs and the network adjusts its variable parameters, the weights and biases, to establish the relationship between the input patterns and outputs. Due to their capability of learning from given patterns, ANNs are very useful for classification tasks such as seizure detection [54] or epileptic spikes [84]. Studies that have applied ANNs to seizure detection are listed in Table 1.

SVMs have been used to find the hyperplane for multidimensional data. The basic idea behind the SVM is to find a hyperplane in a feature space that optimally separates two classes. SVM yields a unique solution that can be shown to minimize the expected risk of misclassifying unseen examples. Training algorithms use the solution of a well known optimization problem constrained to quadratic programming that is computationally efficient and yields global solutions [83]. Like ANNs, SVMs are widely used for epilepsy detection, as listed in Table 1.

6. Performance of seizure detectors

Numerous methods and algorithms have been proposed to automatically detect epileptic seizures. However, there is no standardized performance assessment framework. The performance of seizure detection algorithms should be compared using the same dataset. The metrics employed to compare seizure detection systems vary from publication to publication, with different terms sometimes used to name a given measure. In [85], some classic performance metrics for epilepsy detection are described. There is no consensus about how to report the results; some studies report results as an average over training and testing data, some report results obtained on testing data only. In addition, some report results by averaging over sick and healthy subjects, whereas some report results individually for each category.

Some recent works have begun to overcome this problem. Varsavsky *et al*. [21] proposed some guidelines for validating a detection algorithm and describe a database of scalp and intracranial EEGs validated in St. Vincent's Hospital, Melbourne, Australia. Furthermore, they applied four commercial algorithms (Monitor, CNet, Reveal, and Saab) to the dataset and evaluated and compared the performance of these detectors following their guidelines. They reported true positive rates in a range of 71% to 76% and false positive rates in a range of 9.65 to 2.24 per hour [21].

In addition, Temko *et al*. [86] conducted a very complete review of the performance metrics used for EEG-based neonatal seizure detectors; they describe a classification defined as Epoch-based metrics and Event-based metrics. They proposed a metric called the mean false detection duration (MFDD). Then they report the performance of the detector developed in Temko *et al*. [87] using different the different metrics and show how the performance varies according how it is expressed. Some related work was conducted by Snyder *et al*. [88], who evaluated the statistics of a practical seizure warning system.

6.1 Comparison of seizure detector performance

As mentioned previously, it is very difficult to compare seizure detection algorithms. Table 1 show a summary of databases used in the reviewed works and their characteristics.

To compare published algorithms, works using the same dataset are grouped and their performance in terms of accuracy (ACC), average detection rate (ADR), false detection rate (FDR), sensitivity (SEN), selectivity (SEL), and specificity (SPE) are summarized in Tables 2 and 3. The two validated EEG databases most used by researchers are briefly described below.

Table 2. Performance of detectors that use FSPEEG database.

Reference	Number of patients	Metrics
Schad *et al*. (2008)	FSPEEG-IEEG (6 patients)	SEN = range between 38% and 77% with FDR_{max}
Aarabi *et al*. (2009)	FSPEEG-IEEG	SEN = 68.9% SPE = 97.8% SEL = 58.9% ADR = 82.8%
Orosco *et al*. (2011)	FSPEEG-IEEG	SEN = 41.4% SPE = 79.3% SEN = 69.4% SPE = 69.2%
Raghunathan *et al*. (2011)	FSPEEG-IEEG (5 patients)	SEN = 87.5% SPE = 99.82% ADR = 93.66%

6.1.1 Freiburg seizure prediction EEG database

The Freiburg seizure prediction EEG (FSPEEG) database contains invasive EEG recordings of 21 patients (13 males, 8 females, age = 29.9 ± 11.9 years) suffering from medically intractable focal epilepsy. In 9 patients, the source of epilepsy is located in the temporal lobe; 6 suffer from frontal focal epilepsy; and 1 has parietal epilepsy. The other 5 patients have two epileptic sources. The data were recorded during invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany [89]. In order to obtain a high signal-to-noise ratio and fewer artifacts, and to record directly from focal areas, intracranial grid-, strip-, and depth-electrodes were used. The EEG data were acquired using a Neurofile NT digital video EEG system with 128 channels, a 256-Hz sampling rate, and a 16-bit analog/digital converter. Notch or band-pass filters were not applied in the acquisition stage. The available data include only 6 intracranial EEG channels (3 focal and 3 extrafocal electrodes). This database contains the annotations of the beginning and ending time of the seizures made by experts. Table 2 summerizes the performance of detectors that used the FSPEEG database.

Table 3. Performance of detectors that use Andrzejak database.

Reference	Database	Metrics
Güler and Ü beyli (2005)	Andrzejak-IEEG/SEEG	ACC = 98.68%
Kannathal *et al*. (2005)	Andrzejak-IEEG/SEEG	ACC = 90%
Adeli (2007)	Andrzejak-IEEG/SEEG	Not comparable with others
Polat and Günes (2007)	Andrzejak-IEEG/SEEG	ACC = 98.72%
Subasi (2007)	Andrzejak-IEEG/SEEG	ACC = 95%
Tzallas *et al*. (2007)	Andrzejak-IEEG/SEEG	ACC = 100%
Chua *et al*. (2008)	Andrzejak-IEEG/SEEG	ACC = 88.78%
Guo *et al*. (2010)	Andrzejak-IEEG/SEEG	ACC = 99.6%
Ü beyli (2009)	Andrzejak-IEEG/SEEG	ACC_{RNN} = 98.15% ACC_{MLPNN} = 92.9%
Oweis and Abdulhay (2011)	Andrzejak-IEEG/SEEG	ACC_{EMD} = 94% ACC_{MEMD} = 80%
Orhan *et al*. (2011)	Andrzejak-IEEG/SEEG	ACC = 96.67%
Yuan *et al*. (2011)	Andrzejak-IEEG/SEEG	ACC = 96.5 %

6.1.2 Andrzejak database

The Andrzejak database contains data obtained at the Department of Epileptology, University of Bonn, Bonn, Germany [90]. The data consist of five sets (denoted A-E), each containing 100 single-channel EEG segments of 23.6-s duration. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts. Sets A (eyes open) and B (eyes closed) consist of 10-20 system surface EEG recordings of five healthy volunteers. Sets C, D, and E are from five patients in the intracranial EEG archive of pre-surgical diagnosis. Set D was recorded within the epileptogenic zone, and set C was recorded from the hippocampal formation of the opposite hemisphere of the brain. Sets C and D contain only activity during seizure-free intervals, whereas set E only contains seizure activity. All EEG signals were recorded with the same 128- channel amplifier system, using an average common reference (omitting electrodes containing pathological activity (C, D, and E) or strong eye movement artifacts (A and B)). After 12-bit analog-to-digital conversion, the data were recorded at a sampling rate of 173.61 Hz. The band-pass filter setting was 0.53-40 Hz (12 dB/oct). This database also has annotations by experts for the seizures' time bounds.

Table 3 shows the performance metrics of the detectors that used comparable sets of the Andrzejak database. A review of works that used these signals was made by Tzallas *et al*. [91].

7. Conclusion

The automated detection of epileptic seizures from EEG records has improved with technology. In the reviewed works for this survey, most researchers used either the WT or entropy.

The WT and its combination with other techniques, such as chaos, decomposes the signal in different fixed scales related to the sampling rate of the signal, with the aim of isolating the normal EEG rhythms from epileptic ones, as shown in Table 1. Measures of entropy are used to quantify the level of order (or disorder) of the EEG signal during a seizure. The EMD method, an adaptive decomposition that depends on the frequency content of the signal (instead of a fixed cut-off frequency, as for a wavelet), has been increasing adopted as an alternative to classical time-frequency techniques. Recently, epilepsy detection has utilized multi-way modeling techniques or tensor models that can analyze multimodal data, which capture much more information about complex behaviors. This method allows more than two domains to be analyzed simultaneously, such as with a three-way array epilepsy feature tensor, with modes: time samples × frequency × electrodes.

ANN classifiers are the most commonly used to figure out the patterns described by extracted features. They are used to achieve learning about EEG seizures in order to distinguish them from EEG segments free of seizures. A similar method with the same objective is SVM learning, which has been demonstrated to be faster and easier to implement than ANN with comparable performance results. SVM is thus slowly replacing ANNs in detection.

Progress in epilepsy detection research follows two main lines. One is the development of methods that allow non-invasive and precise detection for diagnostic applications. The principal difficulty to overcome is the presence of artifacts that overlap the signal of interest. The other one is in the neurostimulation and drug delivery field, where the recording and therapy are necessarily invasive but the aim is to achieve onset detection and seizure quantification with maximum exactitude.

Another important issue in the epileptic seizure detection field is the need for a standardization of methods. First, the unification of metrics used to evaluate detector performance is needed in order to make homogenous comparisons. Second, some guidelines are required for the EEG record type (scalp or intracranial) and as well as the duration of these records (it is not the same testing the detector in a record of a few seconds that in a one of an hour long) used to the implementation and testing the algorithms. In general terms, a good epilepsy detector should show at least 80% sensitivity and specificity. For drug delivery systems, the performance must be 100%, whereas for alarm systems, it could be lower. In Table 2, the values of SEN are given, but Schad *et al*. reported a range of values whereas researchers reported an average for all cases [78,13,82,52]. Moreover, these four authors also show other metrics, but some of them are different so it is difficult to state which of these detectors shows the best performance. Raghunatan *et al*. reported the highest SEN and ADR values [82]. In Table 3, almost all works use the ACC as a metric, with values ranging from 88% to 100% (for Tzallas *et al*.) [32]. Therefore, the standardization of the evaluation metrics used for detectors is important. Some researchers have begun to establish guidelines and to look for consensus in the scientific community to achieve these objectives.

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