

REVIEW

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EEG seizure detection and prediction algorithms: a survey

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Abstract

Epilepsy patients experience challenges in daily life due to precautions they have to take in order to cope with this condition. When a seizure occurs, it might cause injuries or endanger the life of the patients or others, especially when they are using heavy machinery, e.g., driving cars. Studies of epilepsy often rely on electroencephalogram (EEG) signals in order to analyze the behavior of the brain during seizures. Locating the seizure period in EEG recordings manually is difficult and time consuming; one often needs to skim through tens or even hundreds of hours of EEG recordings. Therefore, automatic detection of such an activity is of great importance. Another potential usage of EEG signal analysis is in the prediction of epileptic activities before they occur, as this will enable the patients (and caregivers) to take appropriate precautions. In this paper, we first present an overview of seizure detection and prediction problem and provide insights on the challenges in this area. Second, we cover some of the state-of-the-art seizure detection and prediction algorithms and provide comparison between these algorithms. Finally, we conclude with future research directions and open problems in this topic.

1 Review

1.1 Introduction

Epilepsy, which is classified as a neurological disorder that affects the brain, impacts about 2% of the world population leading to a reduction in their productivity and imposing restrictions on their daily life [1]. Diagnosis of epilepsy is done by analyzing electroencephalogram (EEG) signals, as well as patient behavior. EEG signals have two types: scalp EEG and intracranial EEG (iEEG). Scalp EEG signals are usually collected with electrodes placed on the scalp using some sort of conductive gel after treating the scalp area with light abrasion in order to decrease the impedance resulting from dead skin cells. Commonly, 19 recording electrodes in addition to a ground and system reference are placed on the scalp area according to specifications by the International 10–20 system. However, fewer electrodes are used when the EEG signals are recorded for neonates [2]. Each of these electrodes collects an EEG signal, which is centrally recorded for post-processing. On the other hand, in iEEG, electrodes are placed directly on

the exposed surface of the brain during a surgery to record electrical activity from the cerebral cortex. For the seizure detection task in the case of epilepsy patients, it is required to analyze these EEG signals towards a decision of the existence, or absence, of an epileptic seizure. If a seizure exists, further analysis could be made for more understanding of seizure behavior. Most of the research work in the field of seizure detection depends on scalp EEG signals, which are acquired with non-invasive techniques. So, we will adopt the term EEG to refer to scalp EEG throughout the paper.

The seizure detection process can be made on a single- or multi-channel basis [3,4]. Single-channel seizure detection requires selecting the channel containing the strongest EEG signal collected from the closest point to the seizure spot. This selection process depends mainly on activity measures evaluated for the different channels instantaneously such as the local variance. A better treatment to the seizure detection issue depends on incorporating the information from all EEG signals available into the seizure detection process through data fusion, or multi-channel processing techniques [5].

Several studies have been conducted on EEG seizure detection [3,4]. To perform seizure detection on time-domain waveforms, there is a need to create models for the EEG signals, from which features are extracted,

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because treating the signal as discrete-time sequence is not a robust approach for extracting characterizing features. Some algorithms create models for normal and abnormal EEG signals of the patients and use these models in the training process. New signals are tested against these models leading to the decision of seizure or non-seizure activities. Most of the time-domain seizure detection algorithms are patient specific; that is, they are applied to the patient for which training data are extracted. This is intuitively meaningful as each patient has a different nature for his/her EEG signals.

Efforts have also been made to develop seizure prediction algorithms [6,7]. Note that with seizure prediction, it is possible to alert ambulatory patients or caregivers before seizure occurs and causes injury. In addition, seizure prediction could initiate time-sensitive clinical procedures necessary for characterizing epileptic syndromes. It could, also, help in initiating delivery of therapy early enough to attenuate seizure attack and reduce its duration or may even terminate it completely. The endeavor towards fast and simple seizure prediction algorithms has led to the development of a variety of algorithms which will be covered in this paper.

Signal processing has shown a breakthrough with the evolution of several discrete transforms and signal decomposition techniques, because all of these transforms and decompositions have their unique nature. For example, the discrete Fourier transform (DFT) and discrete wavelet transform (DWT) have found popularity in seizure detection and prediction applications. Similarly, the singular value decomposition (SVD) and empirical mode decomposition (EMD) have also found a role in these applications. Even the principal component analysis (PCA) and the independent component analysis (ICA) have found a pre-processing noise removal role in these applications.

Several attempts have been presented in the literature to classify EEG seizure detection and prediction methods. For example, classification into linear and non-linear methods considers variance-based, correlation-based, and simple power spectrum-based methods as linear methods and all other methods as non-linear methods [8-10]. We did not adopt this classification as most of the reviewed methods in this paper are non-linear techniques. Another classification for seizure detection and prediction methods depends on the type of EEG signals used: whether scalp EEG or iEEG. We mentioned in this paper the type of database used for testing each method and the type of the signals in the database.

Tzallas et al. presented a classification of EEG seizure detection methods into pattern recognition methods, morphological analysis methods, parametric methods, decomposition methods, clustering methods, and data mining methods [11]. In this paper, we review some of

the recently developed seizure detection and prediction algorithms along with a comparison study between them adopting another basis for classification of seizure detection and prediction methods depending on the transform domain of operation. It seems that seizure detection and prediction are two different trends, but we look at them from a signal processing perspective with different transform domains. We investigate in our description and classification in this paper the most important seizure detection and prediction algorithms operating in each transform domain. Figure 1 shows a classification of the seizure detection and prediction methods based on the processing domain.

Therefore, we organize the paper as follows. We first begin by the most common methods for seizure detection and prediction: time-domain methods, which are addressed in Section 1.2. Section 1.3 is devoted to frequency-domain seizure detection methods. Wavelet-domain seizure detection and prediction methods are covered in Section 1.4. Sections 1.5 and 1.6 are devoted for seizure detection methods that are based on the EMD and the SVD, respectively. Section 1.7 presents the role of ICA and PCA in seizure detection. A comparison study illustrating seizure detection and prediction methods is given in Section 2.

1.2 Time-domain methods

In general, local activities of EEG waveforms vary from patient to patient; therefore, seizure detection and prediction algorithms are preferred to be patient specific.

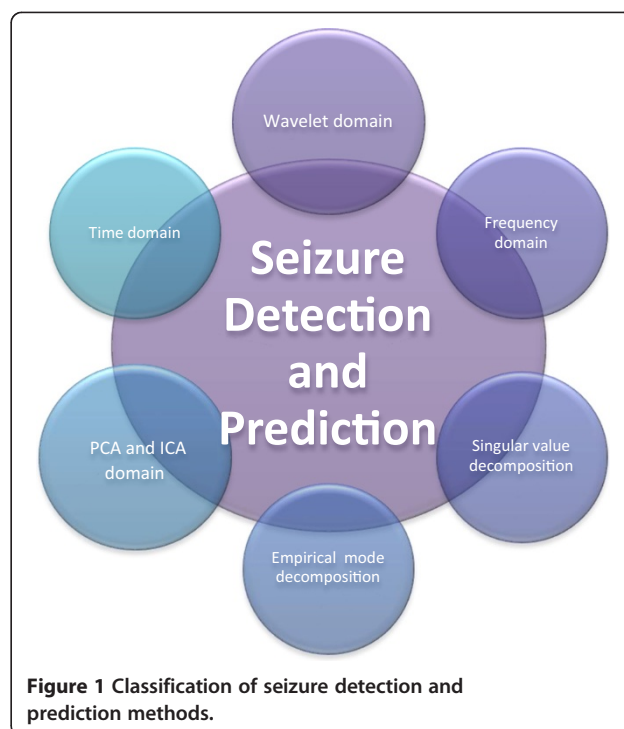


Figure 1 Classification of seizure detection and prediction methods.

Figure 2 shows an example of an EEG signal including a seizure period. It is clear that there is a difference between seizure and non-seizure intervals. As we are able to differentiate between these intervals visually, time-domain detection and prediction methods attempt to differentiate between them automatically, and evaluate the performance using different metrics such as the sensitivity, specificity, accuracy, and false-positive value. These metrics are defined as follows [12]:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100 \quad (1)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100 \quad (2)$$

$$\text{Accuracy} = \frac{TP + TN}{TN + FP + TP + FN} \times 100 \quad (3)$$

$$\text{False positive value} = \frac{FP}{TP + FP} \times 100, \quad (4)$$

where true positive (TP) is the number of seizure epochs determined by both algorithm and experienced physicians, false positive (FN) is the number of seizure epochs which are missed by the algorithm but have been determined by experienced physicians, true negative (TN) is the number of non-seizure epochs recognized by both algorithm and experienced physicians, and false positive (FP) is the number of non-seizure epochs recognized as seizure by the algorithm.

1.2.1 Seizure detection methods

To detect EEG seizures in time domain, there is a need to analyze discrete time sequences of EEG epochs. This analysis can be accomplished through histograms of the epochs. Runarsson and Sigurdsson presented a simple time-domain seizure detection method that is based on tracing consecutive peaks and minima in the signal segment at hand and estimating the histograms for two variables: the amplitude difference and time separation between peak values as well as minima [13]. The features used for classification of an epoch as a seizure or non-seizure are the estimated values of the histogram bins. The authors used a support vector machine (SVM) classifier for this task and achieved an average sensitivity of about 90% on self-recorded data.

Another approach to deal with the EEG seizure detection method in time domain is to compute the signal energy during seizure and non-seizure periods. A better treatment to the energy estimation approach is to estimate the energies of the signal sub-bands not the signal as a whole in order to build a more discriminative feature vector. Yoo et al. adopted this approach and presented an eight-channel EEG acquisition system-on-chip (SoC) that can detect and record patient-specific epileptic seizures [14]. They used a bank of seven band-pass filters covering the frequency range from 2 to 26 Hz on eight channels of the processed EEG signals. Eight highly dynamic analog channels, classification processor, and a 64-KB SRAM have been integrated in the SoC. With this approach, a long-term seizure monitoring and storage

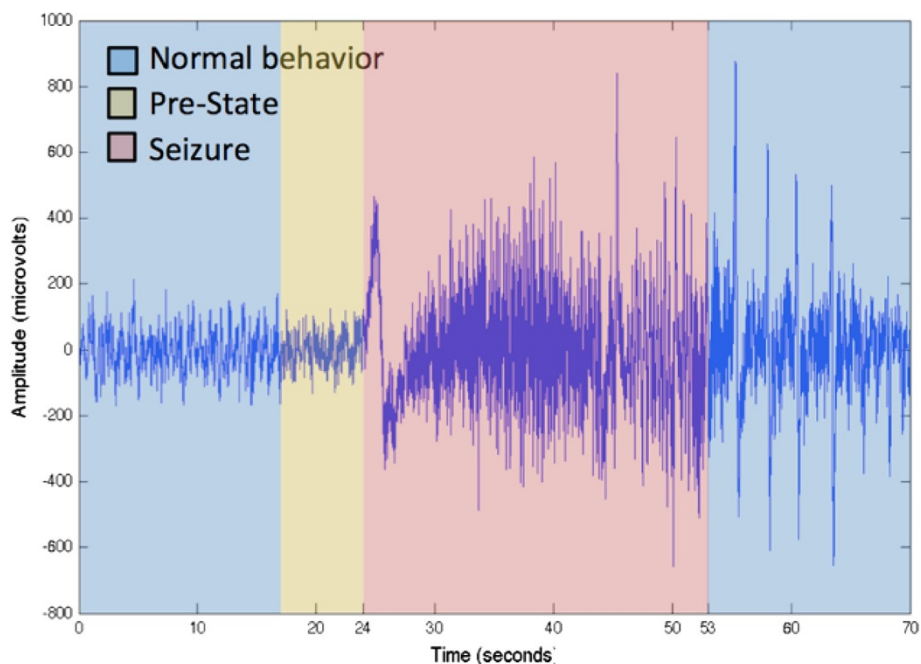


Figure 2 An EEG signal containing a seizure.

device was built. The authors used an SVM as a classifier with a gain and bandwidth (GBW) controller to perform real-time gain and bandwidth adaptation to analog front end (AFE) in order to keep a high accuracy. This classifier is well suited for the hardware implementation. The SoC was tested on CHB-MIT scalp EEG database [15], and it was verified in the presence of a rapid eye blink giving an accuracy of 84.4% with 2.03 μJ /classification energy.

Another approach to deal with time-domain seizure detection is to exploit some discriminating statistics between seizure and non-seizure epochs. Dalton et al. developed a body sensor network (BSN) that can monitor and detect epileptic seizures based on statistics extracted from time-domain signals [16]. These statistics include the mean, variance, zero-crossing rate, entropy, and auto-correlation with template signals. For auto-correlation estimation, they adopted a dynamic time warping (DTW) approach for best alignment between the signal segment to be tested and the template signal. The authors presented a network to be embedded in wearable kinematic sensors and an N810 Internet tablet. Data were recorded from the subjects using kinematic sensors such as triaccelerometer, gyroscope, and magnetic sensor for physical activity monitoring. This algorithm was, then, commercially distributed and a BSN was developed on a Mercury platform. The sensitivity of the proposed algorithm for a dataset of 21 seizures was found to be 91% with a specificity of 84% and battery lifetime of 10.5 h.

1.2.2 Seizure prediction methods

The research work on the issue of time-domain seizure prediction is richer than time-domain seizure detection due to the importance of the seizure prediction problem. We can think of the seizure prediction problem as a detection problem of the pre-ictal state on seizure records. This requires a considerable long inter-ictal state for good prediction results. Similar statistics to those used in seizure detection like the zero-crossing rate can be used for seizure prediction. Zandi et al. used the zero-crossing rate of EEG signal segments to develop a patient-specific seizure prediction method [17,18]. A moving window analysis is used in this method. The histograms of the different window intervals are estimated,

and selected histogram bins are used for classification into pre-ictal and inter-ictal states based on comparison with reference histograms. A variational Bayesian Gaussian mixture model has been used for classification. In this method, a combined index for the decisions taken on selected bins is computed and compared with a pre-defined patient-specific threshold to raise an alarm for coming seizures as shown in Figure 3. This method has been tested on 561 h of scalp EEG containing 86 seizures for 20 patients. It achieved a sensitivity of 88.34%, a false prediction rate of 0.155 h^{-1} , and an average prediction time of 22.5 min.

Aarabi and He [19] developed a time-domain rule-based patient-specific seizure prediction method which consists of three stages: pre-processing, feature extraction, and rule-based decision making. In the pre-processing stage, the iEEG data is filtered using a 0.5- to 100-Hz band-pass filter in addition to a 50-Hz notch filter. Then, the filtered signal is segmented into non-overlapping 10-s segments. Five univariate features (correlation entropy, correlation dimension, Lempel-Ziv complexity, noise level, and largest Lyapunov exponent) and one bivariate feature (non-linear independence) were extracted from each segment in the second stage.

Based on the theory of chaos, the correlation dimension (denoted by ν) represents a dimensionality measure of the space having a set of random points; in our case, EEG signals. For an m -dimensional space containing a set of N points, we have:

$$\vec{x}(i) = [x_1(i), x_2(i), \dots, x_m(i)],$$

$$i = 1, 2, \dots, N$$
(5)

The correlation integral $C(\epsilon)$ can be estimated as [20]:

$$C(\epsilon) = \lim_{N \rightarrow \infty} \frac{g}{N^2},$$
(6)

where g represents the total number of pairs of signals or points having a distance less than ϵ . As the number of points increases and tends to infinity and the distance tends to be shorter or close to zero, the correlation integral, in turn, for small values of ϵ becomes:

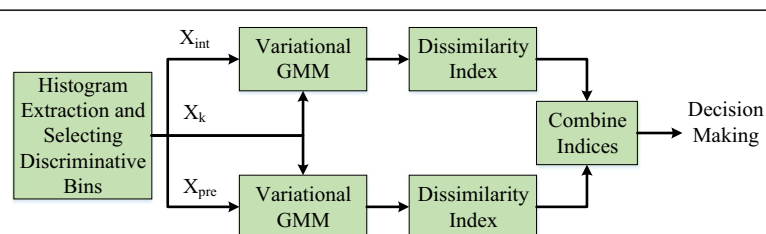


Figure 3 Zandi et al. seizure prediction method.

$$C(\epsilon) \approx \epsilon^\nu \quad (7)$$

If a large number of evenly distributed points exists, a log-log graph of the correlation integral versus ϵ can be used to estimate ν . For objects with higher dimensions, several ways exist for points to be close to each other, and hence, the number of pairs which are close to each other jumps rapidly for higher dimensions [20].

Correlation entropy is a Kolmogorov entropy variant, which is similar to the mutual information between two sequences of data. Large mutual information between an available data segment and stored segments with specific patterns is an indication that the segment at hand belongs to a dataset with similar characteristics to the stored pattern [21]. The Lempel-Ziv complexity is a measure of randomness of data sequences [22]. It counts the number of data patterns with certain characteristics in data segments. For example, if we find enough short patterns with specific mean, variance, or higher-order statistics in an EEG segment, we can classify this segment as a seizure segment.

The Lyapunov exponent of a dynamical system determines the separation rate of very closely related trajectories. Hence, two signal vectors in the phase space with an initial separation of $\delta\mathbf{Z}_0$ will eventually diverge at a rate given by:

$$|\delta\mathbf{Z}(t)| \approx e^{\lambda t} |\delta\mathbf{Z}_0|, \quad (8)$$

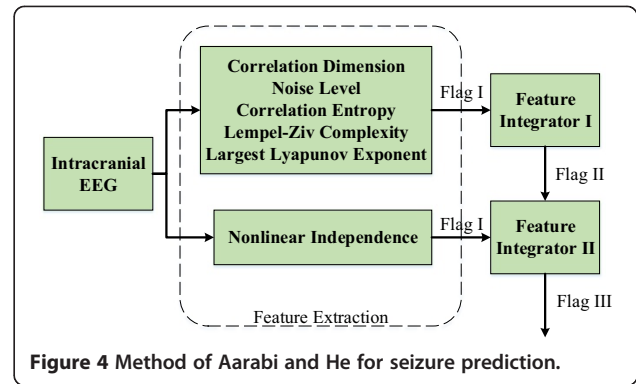
where λ is the Lyapunov exponent. This can be achieved if the divergence can be dealt with within the linearized approximation.

The separation rate differs based on the initial separation vector orientation. The maximal Lyapunov exponent can be estimated as [23]:

$$\lambda = \lim_{t \rightarrow \infty} \lim_{\delta\mathbf{Z}_0 \rightarrow 0} \frac{1}{t} \ln \frac{|\delta\mathbf{Z}(t)|}{|\delta\mathbf{Z}_0|} \quad (9)$$

The limit $\delta\mathbf{Z}_0 \rightarrow 0$ ensures the validity of the linear approximation at any time.

Considering a given segment and feature, if N channels exhibit behaviors like those expected in the feature or segment spatiotemporal profile describing the pre-ictal state of the patient, and if N was greater than a threshold N_{ch} , then this segment is temporarily categorized as a seizure precursor, and hence a flag, labeled as *I*, is raised for the segment as shown in Figure 4. A value is given to this flag by an averaging process for the channels' absolute normalized feature values. The channels selected are those that show similar behavior to the one expected in the spatiotemporal profile of the feature characterizing the pre-ictal state of the patient. The values and location of all flag *I*s are hence stored and given as input into the feature integrator, which integrates decisions for



every segment to accurately locate the seizure precursors. For any signal segment, if M flag *I*s with values that are higher than a certain significance threshold T_{c1} are raised and if M is larger than a certain threshold N_B then another flag which is labeled as *II* is raised. This flag is determined as the average of the values of the flag *I*s. Flag *II*s ensure a higher likelihood of accurate seizure prediction. Flag *II*s are used as input to the feature integrator *II* to obtain a higher-level decision. This feature integrator integrates flag *I*s and flag *II*s as shown in Figure 4. If both flag *I* and flag *II* are raised, then a flag *III* representing a definitive seizure precursor is also raised.

This method has been evaluated using iEEG data from two patients (frontal, temporal lobe origin) from Freiburg Seizure Prediction EEG (FSPEEG) database with a 256-Hz sampling rate and a total of 58 h, and 10 seizures with 50-min pre-ictal at least [24]. The results demonstrated average sensitivities of 90% and 96.5% for patient one and patient two, respectively. The average false prediction rates were 0.06/h and 0.055/h for both patients for prediction horizons of 30 and 60 min.

Schelter et al. presented a new method to minimize the false alarms adopting circadian concepts [25]. A circadian rhythm is defined as any biological operation that reveals an endogenous, entrainable oscillation for 24 h. The authors used the output of the mean phase coherent algorithm, which measures the interaction between pairs of EEG signals, as a seizure predictor, which causes an alarm to be raised if it exceeds a certain threshold. It was assumed that the seizures occur while the patient is sleeping. The false alarms display a circadian dependency with most of the seizure prediction algorithms. The seizure predictability is increased during night due to the large number of seizures. Accordingly, threshold adaptation can be used in day and night to enhance predictability. The authors evaluated this method utilizing iEEG data from eight patients and a total of 1400 h, which include 172 seizures and reported a good prediction performance for 40% of the patients.

Wang et al. proposed an adaptive learning system that interactively learns from the patient and improves its

seizure predictability over time [26]. It is based on reinforcement learning and online monitoring, in addition to adaptive control theory. In this system, a sliding window size of 10 min is used to read continuous multi-channel EEG data with a 50% overlap at each move. Then, k-nearest neighbor (KNN) method is adopted for the classification of the windowed epochs to normal or pre-seizure states based on pre-constructed baselines for both states using pre-specified baseline for normal and pre-seizure states. Finally, according to the prediction feedbacks, the two baselines are updated. This method was evaluated using iEEG data for five patients having temporal lobe epilepsy. The EEG data consisted of 26 channels with a duration range from 3 to 13 h. This method achieved an accuracy of 70% compared to 50% for the Poisson random predictor with a mean interval of λ minutes.

Researchers have proved that symptoms like sleep problems or headaches are observable from the analysis of the iEEG. These symptoms can be utilized as a major tool for seizure prediction. Bedeuzzaman et al. have presented a seizure prediction algorithm with a statistical feature set consisting of mean absolute deviation (MAD) and inter-quartile range (IQR) to predict epileptic seizures [27]. A linear classifier has been used to find the seizure prediction time in pre-ictal iEEGs. A sensitivity of 100% with zero false-positive rate (FPR) in 12 patients and low values of FPR for the rest were achieved using Freiburg iEEG dataset. Average prediction time varied between 51 and 96 min.

The envelope of the EEG signal can be exploited to distinguish between different activities. Li et al. presented a time-domain method for seizure prediction that is based on spike rate estimation [28]. Morphological operations and averaging filters are applied to transform each signal segment to a train of spikes in a way similar to the process of envelope detection. Based on the spike rate, ictal, inter-ictal, and pre-ictal states can be identified through comparison with a certain threshold. This method was applied on 21 patients from Freiburg database, and it achieved a sensitivity of 75.8% and an average false-alarm prediction rate of 0.09/h.

Due to the inherent intra- and inter-patient seizure heterogeneities and EEG non-stationarity, it is difficult to measure the modulations of neuronal network interactions using seizure precursors. To solve this problem,

Stamoulis et al. studied the pre-ictal neuro-modulations corresponding to temporal and/or frontal lobe seizures. They used information theoretic features like entropy and mutual information extracted from two frequency ranges (the range that is less than or equal to 100 Hz and the range that is greater than 100 Hz) of awake scalp EEGs [29]. They succeeded to measure pre-ictal modulations at frequencies greater than 100 Hz with high specificity.

Another approach to process EEG signals in the time domain in order to detect or predict seizure is to create models from the EEG signal segments corresponding to different activities. One of such models is the autoregressive (AR) model, which can be thought of as a data reduction model that transforms the EEG signal segment into few coefficients. Chisci et al. studied the implantation of monitoring and control units on drug-resistant epilepsy patients with AR modeling [30]. They adopted AR modeling with a least-squares parameter estimator for EEG feature extraction in addition to a binary SVM classifier to distinguish between pre-ictal, ictal, and inter-ictal states as shown in Figure 5. This algorithm is computationally simple enabling real-time implementation. Simulation results on the Freiburg database have shown 100% sensitivity with low false-alarm rate. This is attributed to the regularization strategy of the SVM classifier with Kalman post-processing.

The realization of implantable seizure prediction devices that can be used for alerting the patient and taking an action is a very challenging task. Cellular non-linear networks (CNNs), which represent a paradigm for high-speed computations, can be used for this task. Tetzlaff and Senger presented four different CNN-based approaches for epileptic seizure prediction towards an implantable seizure warning device working on any type of simple time-domain features [31]. This method can be used with any of the abovementioned features. The CNNs have been used in these approaches because they consist of locally coupled dynamical systems that can simulate the non-linear phenomena encountered in physical communication.

1.3 Frequency-domain methods

Frequency-domain techniques have been used for EEG seizure detection. Both of the Fourier transform magnitude and phase can be exploited for this purpose. Rana et al. presented a frequency-domain epileptic seizure

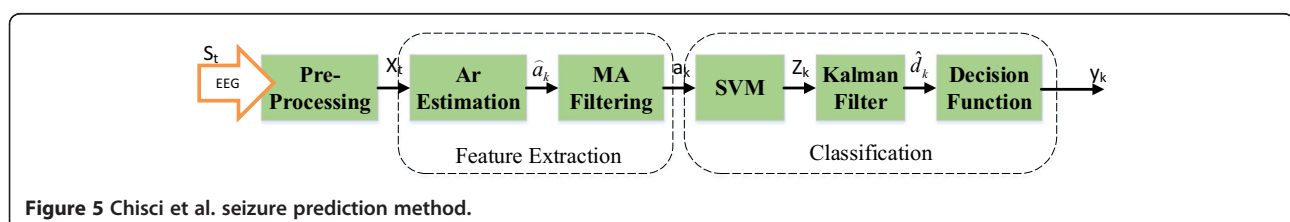


Figure 5 Chisci et al. seizure prediction method.

detection approach depending on the phase-slope index (PSI) of multi-channel EEG signals [32]. If we consider signals $z_i[n]$ and $z_j[n]$, their cross spectrum is given by:

$$S_{ij}(f) = E \left[Z_i(f) Z_j^*(f) \right], \quad (10)$$

where $Z_i(f)$ and $Z_j(f)$ are the Fourier transforms of $z_i[n]$ and $z_j[n]$. Hence, the complex coherence is given by:

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f) S_{jj}(f)}} \quad (11)$$

An unnormalized PSI metric can be defined using complex coherence as follows:

$$\tilde{\Psi}_{ij} = \text{Im} \left(\sum_{f \in F} C_{ij}^*(f) C_{ij}(f + \delta f) \right), \quad (12)$$

where δf is the frequency resolution and F is the frequency band of interest. We can deduce that $\tilde{\Psi}_{ij}$ measures a weighted sum of the slopes of the phase between $z_i[n]$ and $z_j[n]$ over the selected band F [32]. Normalization with the standard deviation is used to determine whether causal influence from $z_i[n]$ to $z_j[n]$ is of significant extent or not.

The PSI computes the measure of interaction between two channels. The authors used the PSI metric to distinguish between seizure and normal activities. The detection performance has been evaluated over five patients having different types of epilepsy with 47 seizures in 258 h of recorded data. The simulation results showed that this algorithm succeeded in the detection of all seizures for four out of five patients, and it achieved a lower false detection rate than two per hour. The results also showed that the channels with strong activity can be determined for each patient.

Khamis et al. used frequency-moment signatures for building a patient-specific seizure detection method [33]. Firstly, experienced electroencephalographs have marked the collected scalp EEG data with seizure events. After that, a filtering process has been performed on the windowed EEG data from electrode differences T6-P4 for the right hemisphere and T5-P3 for the left hemisphere. Power spectral densities of the signals on both hemispheres have been computed and a background removal technique has been used. Moments of these spectra have been used as features for signal classification as seizure or non-seizure. Results reported a sensitivity of 91% and false-alarm rate of 0.02 false positives per hour.

EEG signals are in general non-linear and non-stationary. So, there is a difficulty to characterize different activities of EEG signals with certain mathematical models. To tackle this problem, Acharya et al. presented a modified method for the detection of normal, pre-ictal, and ictal conditions

from recorded EEG signals [34]. This method is based on four entropy features for classification: phase entropy 1 (S_1), phase entropy 2 (S_2), approximate entropy (ApEn), and sample entropy (SampEn). The phase entropies are estimated from the higher-order spectra of EEG signal epochs as discriminating features for ictal, pre-ictal, and inter-ictal activities. The approximate and sample entropies are logarithmic metrics that determine the closeness and matching between the incoming EEG signal pattern and the recorded templates. These features are extracted from EEG signals and fed to seven different classifiers for comparison: SVM, fuzzy Sugeno classifier (FSC), probabilistic neural network (PNN), KNN, naive Bayes classifier (NBC), decision tree (DT), and Gaussian mixture model (GMM). The obtained results with this method showed the superiority of the Fuzzy classifier, which achieved an accuracy of 98.1%.

1.4 Wavelet-domain methods

Wavelets have been widely used in the field of EEG signal analysis, especially for seizure detection and prediction. The wavelet transform in itself can be regarded as some sort of sub-band decomposition, but with down-sampling. The wavelet transform can be implemented on analog as well as digital signals. We are more interested in the DWT. The DWT can be implemented with low-pass (LP) and high-pass (HP) filtering in addition to a decimation process, and it must be invertible as shown in Figure 6a [35]. The DWT can be implemented with a single level or multi levels as shown in Figure 6b, c. For the multi-level wavelet decomposition, further decompositions up to the required level are performed on the low-pass branch only. Another implementation of wavelet analysis is the wavelet packet transform, which performs further decomposition on the low-pass and high-pass branches.

The wavelet decomposition and reconstruction filters $H_0, H_1, G_0,$ and G_1 must satisfy the perfect reconstruction (PR) condition. These filters can be obtained by solving the following equation [35]:

$$\begin{aligned} Y(z) &= \frac{1}{2} \{X_0(z) + X_0(-z)\} G_0(z) + \frac{1}{2} \{X_1(z) + X_1(-z)\} G_1(z) \\ &= \frac{1}{2} X(z) \{H_0(z) G_0(z) + H_1(z) G_1(z)\} \\ &\quad + \frac{1}{2} X(-z) \{H_0(-z) G_0(z) + H_1(-z) G_1(z)\} \end{aligned} \quad (13)$$

The main idea of using the wavelet analysis for EEG seizure detection and prediction is extracting discriminating features from appropriate sub-bands to be used for further classification.

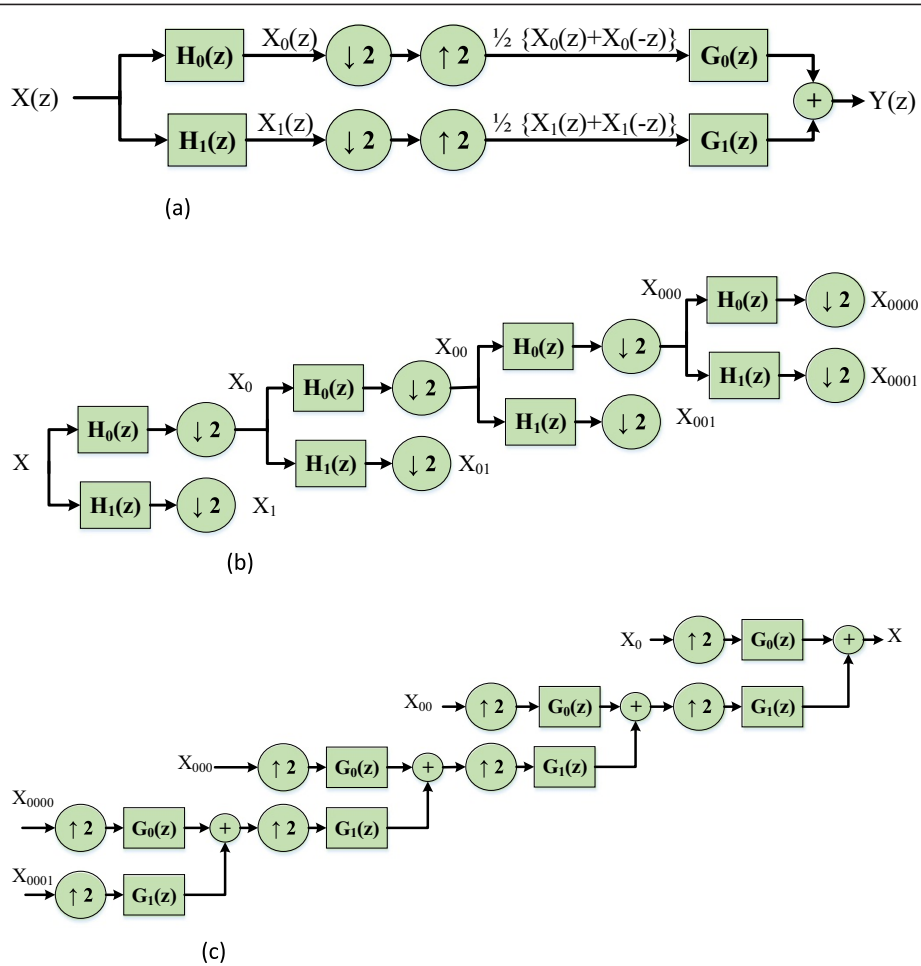


Figure 6 Wavelet decomposition and reconstruction. The down arrow is down-sampling by 2, and the up arrow is up-sampling by 2. (a) The two-band decomposition-reconstruction filter bank. (b) Multi-level wavelet decomposition tree. (c) Multi-level wavelet reconstruction tree.

1.4.1 Wavelet-domain seizure detection

The main challenge in wavelet-based EEG seizure detection is the determination of the appropriate wavelet decomposition level and the selection of the features from certain sub-bands for discrimination between seizure and non-seizure periods. Zhou et al. presented a wavelet-based seizure detection method that depends on lacunarity and fluctuation index as features with Bayesian linear discriminant analysis (BLDA) [12]. The lacunarity is a measure of heterogeneity used in fractal analysis. In this method, the authors first decompose the EEG epochs into five wavelet sub-bands. Three sub-bands with scales 3, 4, and 5 are chosen for further processing. For feature extraction, lacunarity and fluctuation index are computed within the frequency bands. If $p(m, l)$ denotes the probability of points, whose amplitude is equal to m , l represents the length of EEG epochs, A is the minimum amplitude value, and B is the maximum amplitude value, then the equation below holds [12]:

$$\sum_{m=A}^B p(m, l) = 1 \quad (14)$$

After calculating,

$$M_1(l) = \sum_{m=A}^B mp(m, l) \quad (15)$$

$$M_2(l) = \sum_{m=A}^B m^2 p(m, l) \quad (16)$$

The lacunarity can be obtained as:

$$la(l) = \frac{M_2(l) - [M_1(l)]^2}{[M_1(l)]^2} \quad (17)$$

After feature extraction, BLDA is used to classify the seizures. The BLDA tries to minimize the risk associated with the classification decision. It can deal with high

dimensionality and noisy datasets, assuming a linear relation between targets t and feature vectors x from one side and additive white Gaussian noise n from the other side in Bayesian regression. Post-processing, such as smoothing, and multi-channel decision fusion are applied to enhance the detection accuracy of the BLDA. The performance of this method was investigated on Freiburg EEG database, and it achieved a 96.25% sensitivity with 0.13/h false detection rate.

Another five-level wavelet decomposition method for seizure detection was developed by Liu et al. [36]. This method works on multi-channel iEEG signals. Three wavelet sub-bands are selected for further processing. The extracted features from these sub-bands are the relative amplitude, relative energy, coefficient of variation, and fluctuation index from the selected frequency bands. The coefficient of variation is the ratio between the standard deviation of a decomposed sub-band and the square of its mean. The fluctuation index is a measure of the intensity of a decomposed sub-band. An SVM classifier is used in this approach, and some sort of post-processing is implemented to enhance the detection performance with smoothing, multi-channel decision fusion, and collar processing. The collar processing is technique aiming to maintain the data continuity during processing. The performance of this method has been tested on 509 h for 21 epilepsy patients. Experimental results have shown that this method achieved a 94.46% sensitivity, a 95.26% specificity, and a 0.58/h false detection rate on long-term iEEG.

The five-level wavelet decomposition was also adopted by Panda et al. with an SVM classifier for seizure detection from background EEGs [37]. This classifier was tested on a healthy subject with open eyes, a healthy subject with closed eyes, and an epilepsy patient. The extracted features for signal classification are energy, standard deviation, and entropy. The simulation results revealed an accuracy of 91.2% in seizure activity detection. Khan et al. proposed a similar approach for seizure detection, but with relative energy and a normalized coefficient of variation (NCOV) as features [38]. It works on wavelet coefficients acquired in the frequency range of 0 to 32 Hz as follows:

1) The COV is estimated as:

$$COV = \frac{\sigma^2}{\mu^2} \quad (18)$$

where σ^2 is the epoch variance and μ is the epoch mean.

2) The RCOV is estimated as:

$$RCOV = \frac{COV_e(n)}{COV(l)} \quad (19)$$

where $COV_e(n)$ is the epoch coefficient of variation and $COV(l)$ is the background coefficient of variation.

3) The NCOV is evaluated as:

$$NCOV = \frac{\sigma^2}{\mu_a}, \quad (20)$$

where μ_a represents the mean of the absolute values of the wavelet coefficients. The obtained results with the NCOV are better than those obtained using the COV only.

Wang et al. used Neyman-Pearson rules and an SVM classifier for seizure detection as shown in Figure 7 [39]. This method depends on the wavelet coefficients in addition to the ApEn in the wavelet domain as extracted features, and the detection is performed using Neyman-Pearson rules with an SVM. The approximate entropy is an entropy metric that takes into consideration the ordering of the points of the discrete time sequence at hand, and hence, it is a good measure for the regularity of the data sequence. Simulation results have shown a detection accuracy of 98% and a false detection rate of 6%.

Zainuddin et al. investigated the use of wavelet neural networks (WNNs) based on wavelet basis functions for seizure detection [40]. Firstly, the wavelet transform of EEG signals is estimated, and maximum, minimum, and standard deviation of the absolute values of the wavelet coefficients in each sub-band are extracted as features. These features are then fed to trained WNNs. The Gaussian, Mexican Hat, and Morlet wavelet activation functions have been investigated for classification. A cross-validation approach have been adopted in the

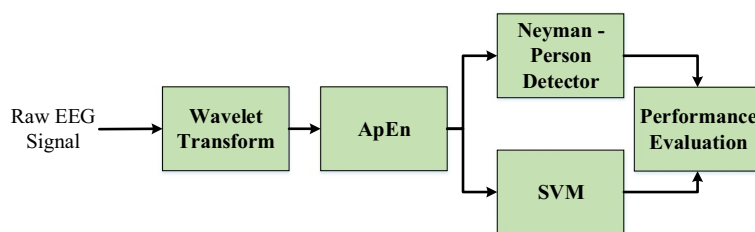


Figure 7 Wang et al. method for seizure detection.

simulation experiments. Simulation results revealed that the best performance was obtained with WNNs employing a Morlet wavelet activation function with order 4 Daubechies wavelet for feature extraction. The authors have carried simulation experiments on the University of Bonn database for scalp EEG signals [41]. The simulation results reported sensitivity and accuracy up to 98% with such combination.

Niknazar et al. presented a wavelet-based method for epileptic seizure detection that adopts recurrence quantification analysis (RQA) on EEG recordings and their delta, theta, alpha, beta, and gamma sub-bands extracted through a four-level Daubechies wavelet transform [42]. The RQA is well-suited for non-linear data analysis. It quantifies the number and duration of recurrences of the EEG signals based on phase space trajectories. The phase space is built on estimating a time delay and an embedding dimension, which are the features corresponding to each EEG signal state. The authors adopted an error-correcting output coding (ECOG) classifier for discriminating between three states: healthy, inter-ictal, and ictal. This method achieved an accuracy of 98.67%.

Daou and Labeau presented a wavelet-based approach for EEG signal compression and seizure detection, simultaneously [43]. The compression is performed with the set partitioning in hierarchical trees (SPIHT) algorithm. The SPIHT codes the LP and HP components of the signals with binary sequences. A dictionary is built for these binary sequences of normal and seizure activities. The seizure detection process is performed for each incoming segment by correlation estimation with the binary codes of normal sequences in the dictionary. If low correlation is detected, correlation estimation is performed with binary sequences of the HP components of seizure segments to ensure seizure activity. This method achieved an accuracy of about 90%.

Statistical analysis revealed that the spectra of normal EEG signals follow an inverse attenuation law over the bands of interest, which means that there are self-similar fluctuations in EEG signals over a multiplicity of scales. Based on this idea, Mehta et al. presented a scale-invariant seizure detection method [44]. In this method, the onset is detected, when the scale invariance is lost, which means that the slope of the regression line on a logarithmic plot for the wavelet scales 6 to 2 decreases.

Shoib et al. presented a low-energy scalable processor for directly analyzing EEG signals acquired through compressive sensing [45]. This work adopts wavelet energy features. It studies the effect of compressive sensing on seizure detection performance showing a reduction of only 4% in detection sensitivity and an increase of only 0.15/h in false-alarm rate and 1 s in latency compared to baseline performance. The main advantage of this method is energy saving archived through compressive sensing.

Zandi et al. presented a wavelet packet real-time seizure detection algorithm working on scalp EEG signals [46]. They developed a patient-specific metric to differentiate between seizure and non-seizure states in the 1- to 30-Hz frequency range based on wavelet coefficients of seizure and non-seizure references. A combined seizure index (CSI) is derived from all EEG signal channels depending on the rhythmicity and relative energy of signal epochs for classification as seizure or non-seizure. A majority voting rule is used on the decisions from all channels to generate the CSI and raise an alarm when a seizure is detected. This algorithm was tested on 14 patients having 75.8 h with 63 seizures, and it achieved a sensitivity of 90.5%, a median detection delay of 7 s, and a false-alarm rate of 0.51 h^{-1} .

1.4.2 Wavelet-domain seizure prediction

The same concepts of wavelet signal analysis used for seizure detection can be extended to seizure prediction, but with the target this time as the detection of the pre-ictal state. In general, EEG signals containing seizures are build up of constantly changing bursting levels. This signal nature enables discrimination between different signal activities from wavelet sub-bands. The residual sub-band wavelet entropy (RSWE) can be directly used to estimate the entropy of bursts from the sub-bands as proposed by Paul et al. [47]. The wavelet decomposition equation for an EEG signal using a sliding window of index m is given by:

$$s(t) = \sum_{\tau=-\infty}^{\infty} a_L^m(\tau) \phi(2^{-L}t-\tau) + \sum_{l=1}^L \sum_{\tau=-\infty}^{\infty} C_l^m(\tau) \psi(2^{-l}t-\tau), \quad (21)$$

where $C_1^m(\tau), C_2^m(\tau), \dots, C_L^m(\tau)$ are the wavelet coefficients. The sequence $\{a_L^m(\tau)\}$ is the coarser-resolution signal for a high-level decomposition. The authors experimented lower and higher numbers of levels and found that the five levels are the optimum choice.

The relative wavelet energy (RWE) of the wavelet coefficients is used to derive a sub-band wavelet entropy (SWE) feature. For a sliding window with index m , the field potential (FP) is given by [48]:

$$E_l^m(\tau) = |C_l^m(\tau)|^2 \quad (22)$$

The wavelet coefficients total energy is given by:

$$E_{rmtotal}^m = \sum_l \sum_{\tau} E_l^m(\tau) \quad (23)$$

The RWE can be expressed with normalization as:

$$p_l^m(\tau) = \frac{E_l^m(\tau)}{E_{r\text{total}}^m} \quad (24)$$

The SWE at scale l can be defined with a probabilistic approach as:

$$H(C_l^m) = \sum_{\tau} p_l^m(\tau) \log p_l^m(\tau) \quad (25)$$

The l th level RSWE of the n th frame is given by:

$$J(C_l^{m,n}) = H(C_l^{m,n}) - \frac{1}{N_o} \sum_{n=1}^{N_o} H(C_l^{m,n}), \quad (26)$$

where $C_l^{m,n}$ represents the wavelet coefficients of the n th frame in the m th window.

For the estimation of the RSWE, a sliding window of 1-min length has been used assuming that the FP is stationary during this window. It was also assumed that the background FP fluctuations stay statistically unchanged for frames of 5-s length during the main sliding window. On the other hand, the FP fluctuations have another component that is statistically variant over the 5-s frames. Hence, an averaging process is performed on the background entropy components estimated in the main window. Consequently, resulting residual entropy corresponds only to the bursting components. A key observation on this approach is that there is an increment in the mean cortical RSWE during the transition from the pre-ictal to inter-ictal period. This increment can be used with an efficient slope change detector and used for early seizure prediction.

Hung et al. developed a very large scale integration (VLSI) setup of wavelet-based seizure prediction algorithm using the correlation dimension (D_c) and its correlation coefficient [48]. Their system comprises arithmetic functional and control units. The arithmetic functional units are the DWT, correlation dimension, correlation coefficient, and seizure prediction. The DWT of the pre-processed signal is estimated to decompose it into four sub-bands (0 to 63 Hz, 64 to 128 Hz, 0 to 1 Hz, and 32 to 64 Hz). The higher-frequency sub-bands are then represented in the phase space. The correlation dimension and correlation coefficient are estimated in the phase space as seizure prediction features. The authors evaluated their method utilizing iEEG data from 11 patients of the Freiburg database with 256-Hz sampling rate. Their method achieved an average of 87% sensitivity, 0.24/h false prediction rate, and in average a 27-min warning time ahead the ictal.

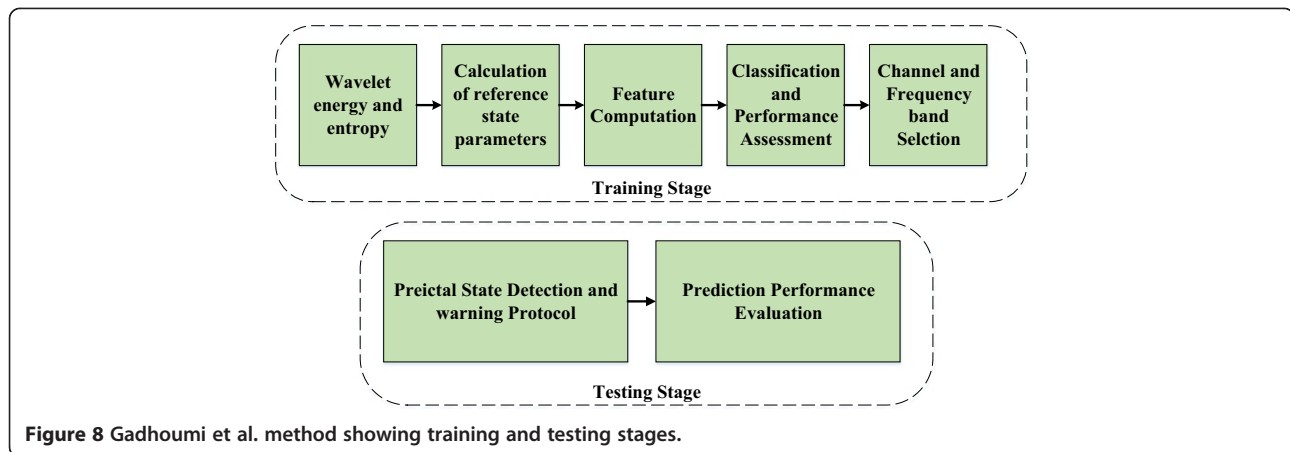
Chiang et al. developed an online wavelet-domain retraining method to improve the seizure prediction by enlarging the training dataset gradually [49]. Their method is based on the method of Mirowski et al. [50] that uses non-linear interdependence, cross-correlation,

difference of Lyapunov exponents, and phase locking. Post-processing is used in this method to reduce the false-alarm rate if two consecutive patterns are classified as pre-ictal. The authors evaluated their method using three datasets: Freiburg database, CHB-MIT database (eight patients), and National Taiwan University Hospital database for scalp EEG (one patient) [51]. This method achieved sensitivities of 74.2% and 52.2% on intracranial and scalp databases, respectively. It also achieved an improvement in the sensitivity of off-line training on both databases by 29.0% and 17.4%, respectively.

Rojas et al. presented a seizure prediction method depending on brain excitability recognized with couplings between low-frequency phases (delta: 0.5 to 33 Hz, theta: 3 to 8 Hz) and high-frequency amplitudes (low gamma: 40 to 70 Hz, high gamma 70 to 140 Hz) of brain waves [52]. They evaluated this method on 20 patients from EPILEPSIAE scalp EEG database [53]. The EEG data was recorded using either depth or subdural stereotactic electrodes at a sampling rate 1,024 Hz with a total of 267 seizures and more than 3,400 h of inter-ictal activities. They found that in 50% of the cases, their predictor performed better than the random predictor, which is based on Poisson process, with an average sensitivity 98.9%, false rate of 1.84/h, and pre-ictal window length of 10 min.

Gadhoumi et al. presented an iEEG-based seizure prediction method based on measuring the similarity with a reference state as shown in Figure 8 [54]. In the validation of this method, 1,565 h of continuous iEEG data for 17 patients having mesial temporal lobe epilepsy were used. These recordings have 175 seizures. Distance, inclusion, and persistence features are extracted in this method from the continuous wavelet transform of EEG recordings to discriminate between pre-ictal and inter-ictal states. The distance is a Euclidean distance between the center energy and the rest of energy points computed from the wavelet coefficients. Inclusion is the percentage of energy points with entropy confined to a pre-specified distance. Inclusion represents the time interval in which the maximum number of successive 2-s points has energy and entropy profiles confined to the pre-specified distance. An SVM classifier has been used in the signal discrimination and a comparison has been performed with a random statistical predictor. Simulation results have shown a sensitivity of 85% and a false-alarm rate of 0.35/h. The authors came to a conclusion that state similarity measures can be used for seizure prediction above chance in 41% of the patients.

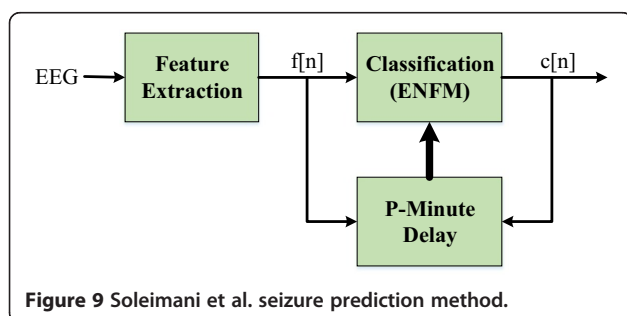
Gadhoumi et al. also presented a method to discriminate between pre-ictal and inter-ictal states using features extracted from the high-frequency sub-bands of iEEG signals [55]. The selected features are the wavelet energy and entropy extracted from different signal epochs. The



estimated energy and entropy are compared to reference energy and entropy for pre-defined signals with pre-state and seizure activities, and based on distance metrics, the decisions are taken from different channels and fused. Sensitivity and false-alarm rate evaluation revealed a sensitivity of about 80% and a false positive rate ranging from 0.09 to 0.7 for different patients.

Wang et al. presented a wavelet-based online adaptive seizure prediction system [56]. This system adopts Lyapunov exponent, correlation dimension, Hurst exponent, and entropy features extracted from the wavelet transform of EEG recordings. It adopts also a KNN classifier. The adaptation is performed in this system with a reinforcement learning algorithm. A 150-min prediction horizon used on ten patients and the system achieved the best prediction results of 73% sensitivity and 67% specificity.

Soleimani et al. presented a simple and fast adaptive online method for the detection of pre-ictal patterns depending on multiple features as illustrated in Figure 9 [57]. These features are time domain and wavelet domain. The time-domain features are the curve length, the average energy, non-linear energy, six-order power at time n , kurtosis, skewness, and variance. The wavelet-domain feature include mean of absolute values, average power, standard deviation, absolute mean of sub-bands



of a fifth level Daubechies wavelet transform. In this method, a neuro-fuzzy model is used for combined features learning in an adaptive manner. An adaptive tuning process is used in the classifier operation to build a personal seizure predictor. Freiburg database of intracranial recordings for 21 patients has been used with this classifier. Simulation results revealed that on-line adaptive seizure prediction achieves better results than off-line non-adaptive seizure prediction. The percentage of prediction was 99.52%, and the FPR was 0.1417/h.

It is possible to use some time-domain features with wavelet-domain features to enhance the detectability of seizures. Costa et al. have selected 14 features for efficient seizure prediction from EEG recordings [58]. These features include energy estimated from time-domain signals, energy variation, energy level, non-linear statistics, and sub-band energies extracted from the wavelet sub-bands. They used a neural network classifier for signal classification into four states: pre-ictal, ictal, inter-ictal, and post-ictal. They achieved an average specificity of 99%, an average sensitivity of 83%, and an average accuracy of 96% on patient records from Freiburg database. Moghim and Corne compared the Costa et al. results with multi-class SVM and evolved neural network classifiers [59]. They carried out this comparative study on one patient (patient 2: 135 min, 3 seizures, 30 to 40 min before and 10 min after each seizure) from Freiburg database, and they reported that 8- to 10-min detection before the onset can be achieved with reasonable specificity and sensitivity.

1.5 Empirical mode decomposition

The EMD is a signal decomposition, which transforms a signal into a group of intrinsic mode functions (IMFs). For EEG seizure detection, these IMFs show different behavior with normal and abnormal activities in the signals. Features can also be extracted from the IMFs and

tested for seizure detection and prediction. The steps to extract these IMFs from an original signal $x(t)$ are summarized below [60]:

1. Determine the signal envelope by maxima and minima point estimation and interpolate between them.
2. The local mean, $m(t)$ is estimated using the envelope as follows:

$$m(t) = \frac{e_{\min}(t) + e_{\max}(t)}{2} \quad (27)$$

where $e_{\min}(t)$ and $e_{\max}(t)$ are the envelope minimum and maximum values respectively.

3. The mean is subtracted from the original signal to get $h(t) = x(t) - m(t)$.
4. If $h(t)$ does not satisfy the IMF criteria of a difference of at most 1 between the number of extrema (maxima and minima) and number of zero crossings, we go to step 1 with $h(t)$ as a new input.
5. The obtained $h(t)$ is stored as an IMF in case it satisfies the criteria of an IMF, $c_i(t) = h(t)$. Hence, this IMF is removed from the original signal by subtraction, $r(t) = x(t) - c_i(t)$, where i is the i th IMF.
6. Similar steps are repeated beginning from step 1.

The Hilbert transform (HT) is performed on each IMF to get $\tilde{c}_i(t)$ provided that $z(t) = c_i(t) + j\tilde{c}_i(t)$ is analytic. Both amplitude and phase of $z(t)$ are given by:

$$A(t) = \sqrt{c_i^2(t) + \tilde{c}_i^2(t)} \quad (28)$$

$$\phi(t) = \arctan \left[\frac{\tilde{c}_i(t)}{c_i(t)} \right] \quad (29)$$

The instantaneous frequency is estimated as:

$$\omega = \frac{d\phi(t)}{dt} \quad (30)$$

1.5.1 EMD seizure detection

Eftekhari et al. used the EMD approach for seizure detection [60]. They adopted features such as the frequency rise at the seizure onset with the EMD in a patient-specific manner. Their simulation results have shown that the Hilbert transform can be used to decompose EEG signals into components, from which features can be extracted for seizure onset detection.

Tafreshi et al. evaluated the performance of the EMD in discriminating epileptic seizure data from normal data using means of the absolute of the IMFs as features [61]. They compared this approach for feature extraction with wavelet features using both multi-layer perceptron (MLP) and self-organizing map (SOM) neural networks.

Results have shown that the EMD approach is better in performance than the wavelet approach with success rates up to 95%, and they revealed that four empirical modes are enough to obtain good results. In addition, the results have shown that a window length of 1,500 samples is appropriate to obtain good recognition rates. The MLP networks are superior in performance to the SOM networks.

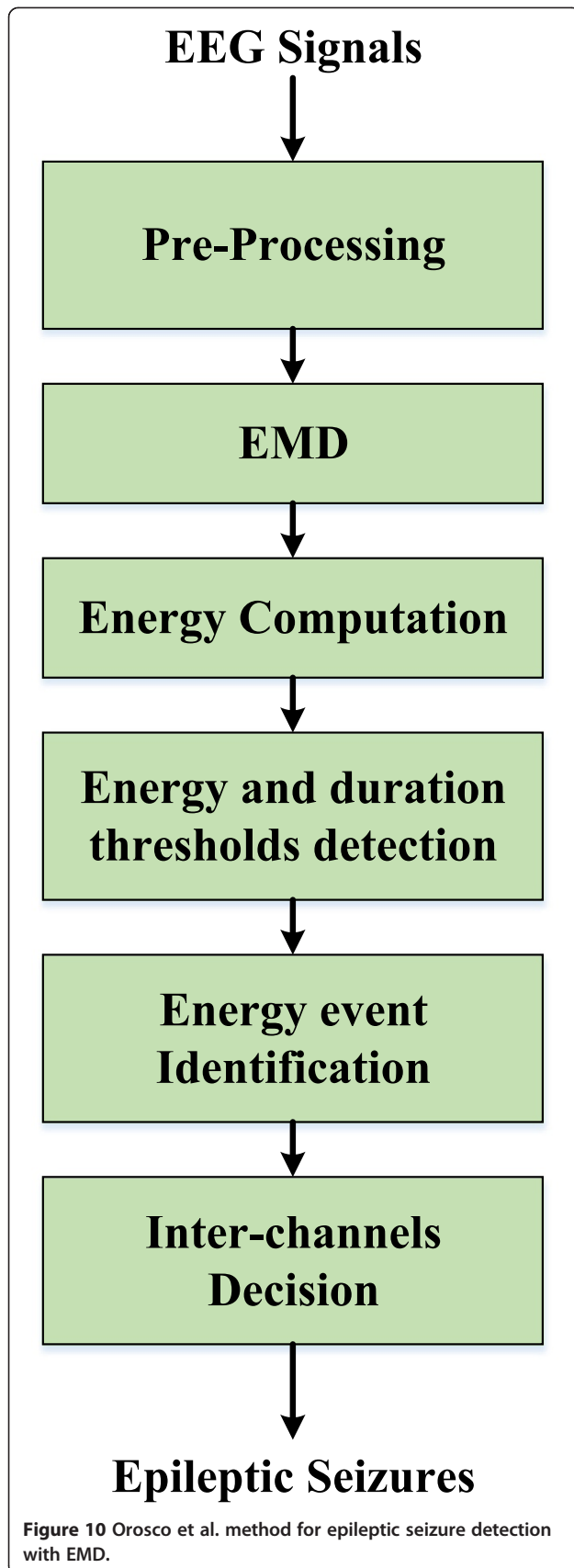
Orosco et al. presented a seizure detection approach based on the energies of IMFs as discriminating features between seizure and non-seizure activities as shown in Figure 10 [62]. In this approach, the IMF energies are compared with certain thresholds for decision making. It was tested on nine patient records from Freiburg database with invasive nature. The obtained sensitivity and specificity were 56.41% and 75.86%, respectively, using 39 seizure records.

Guarnizo and Delgado presented a modified EMD approach, in which mutual information is used for feature selection in the EMD domain [63]. These features include the average or instantaneous frequency and amplitude for all EMD components. Higher-order statistics such as the skewness and kurtosis in addition to Shannon's entropy have been selected as features extracted from the energy estimated with the Teager energy operator (TEO) over all EMD components [64-66]. This approach adopts a linear Bayes classifier and it achieved an accuracy of 98%.

Alam and Bhuiyan presented a seizure detection method depending on extracting kurtosis, skewness, largest Lyapunov exponent, variance, approximate entropy, and correlation dimension from the EMD of EEG signals with artificial neural network classifiers [67,68]. This method achieved a 100% sensitivity in seizure detection and has shown a superiority as compared to time-frequency techniques and band-limited techniques in the computational complexity.

Bajaj and Pachori presented an EMD-based seizure detection method to detect focal temporal lobe epilepsy [69]. In this method, they used Hilbert transformation of IMFs which were obtained by an EMD process. Epileptic seizures are then detected based on the instantaneous area estimated from the trace of analytic IMFs of EEG signals. The performance of this epileptic detection method was evaluated on Freiburg database and achieved a sensitivity of 90%, a specificity of 89.31%, and an error detection rate of 24.25%.

The local mean of EMD can be used as a statistical feature for seizure detection. This local mean is obtained by averaging the lower and upper envelopes obtained through interpolation between the local maxima and minima. If these local maxima and minima are not defined as in the case of multivariate signals, another alternative which is the multivariate EMD (MEMD) can be used instead. The MEMD depends on signal projections



along n -dimensional spaces to generate n -dimensional envelopes, which are then averaged to get the local mean. The projection direction vectors are based on spherical and polar coordinates. To sample the n -sphere, quasi-Monte Carlo low-discrepancy sequences are exploited for sampling enhancement. This style of sampling is non-uniform but not random. Its objective is to get the most useful samples over a certain space. The other steps of the algorithm to estimate the MEMD are similar to the standard EMD algorithm. The use of the MEMD enables the multi-channel EEG signal decomposition into narrow frequency bands that can be analyzed separately for better detectability of seizures. In addition, the mean frequency of the signal segments can be used as a discriminative feature for seizure detection. This mean frequency can be calculated by applying the Hilbert transform on the resulting IMFs. Rehman et al. investigated the use of the MEMD with the mean frequency as possible features for EEG seizure detection [70], but this proposal needs further studies.

1.5.2 EMD seizure prediction

Qi et al. suggested the use of EMD for seizure prediction with a new feature, called IMF-VoE. This feature combines three IMFs obtained from the EMD of an EEG signal in addition to the range variance between upper and lower envelopes (VoE) in the EMD domain [71]. The authors tested this method using 80.4 h of EEG data containing ten seizures for four patients. This method achieved a sensitivity of 100% and a false detection rate of 0.16/h. The estimated average time delays were 19.4, 13.2, and 10.7 s for false detection rates of 0.16, 0.27, and 0.41/h, respectively, using different thresholds.

1.6 SVD methods

The SVD operating on a matrix A decomposes it into matrices U , S , and V [72,73]:

$$A = USV^T \quad (31)$$

The matrices U and V are orthogonal such that $U^T U = I$, and $V^T V = I$. $S = \text{diag}(\sigma_1, \dots, \sigma_p)$, where $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_p \geq 0$ is the matrix of SVs of A . The matrix U contains the left singular vectors of A , while the matrix V contains the right singular vectors of A . An important characteristic of the SVD that can be used in EEG seizure detection is that the SVs are not largely affected by little disturbances in the matrix A . This property can be used for the detection of seizure activities taking into consideration the slight variations between seizures [72,73].

Vanrumste et al. developed an SVD-based algorithm for EEG seizure detection [74]. In this algorithm, the EEG is segmented into overlapping epochs, which are formulated as 2-D arrays to allow SVD. Most of the

signal energy, which differs from seizure to non-seizure activities, is concentrated in the first SVs. After that, an EEG dipole source analysis adopting a single-dipole model is implemented on the EEG segments. This analysis assumes that each spike results from a dipole in the human brain and performs a localization process for the position of this source dipole [75]. This yields dipole parameters in addition to a relative residual energy (RRE). A seizure alarm on an epoch is raised if the SVD indicates a dominant source and the RRE has a low value. The algorithm has been investigated on synthetic EEG signals obtained from two sources, synchronous and asynchronous. In the synchronous case, the main metric is the RRE, and in the asynchronous case, the SVD and RRE are of major concern. The same algorithm has been investigated with real EEG signals having two spikes and an eye-blink artifact. The algorithm has shown that the RRE was always low for all three events.

Shahid et al. presented an algorithm based on SVD for the detection of seizures [76]. In this algorithm, the SVD is applied sequentially on a sliding window of the EEG signal of 1-s width and then r singular values are obtained and used to indicate sudden changes in the signals. EEG recordings of four pediatric patients with 20 seizures have been used to validate this algorithm, and the results indicated the sensitivity of the SVs to the changes in the EEG signals due to epileptic seizure.

1.7 ICA and PCA methods

The SVD methods presented in above section adopt a strategy of transforming the 1-D data to a 2-D array, but the PCA and ICA techniques in this section adopt a covariance approach to obtain the PCs. ICA is signal decomposition that transforms a multivariate signal into additive, non-Gaussian, and statistically independent components [77]. The main principle that the ICA depends on is the maximization of the statistical independence between the estimated components. This can be guaranteed through either mutual information minimization or non-Gaussianity maximization. For mutual information minimization, measures like Kullback–Leibler divergence and maximum entropy are exploited. On the other hand, for non-Gaussianity maximization, central limit theorem, higher-order statistics such as kurtosis, and negentropy are used [77]. The ICA depends mainly on some pre-processing techniques such as mean removal, whitening, and dimensionality reduction. Both whitening and dimensionality reduction can be achieved with PCA or SVD. Whitening ensures an equal treatment to all dimensions before the algorithm is run.

1.7.1 Seizure detection

Both ICA and PCA have been used as signal separation algorithms to enhance the detectability of seizures from

EEG signals by separating artifacts from these signals [78]. Xie and Krishnan proposed a multi-scale PCA method combining both DWT and PCA for de-noising and EEG signal decomposition [79]. They developed an empirical classification (EC) method using spatial and temporal features. This method achieved high classification accuracy.

1.7.2 Seizure prediction

Miri and Nasrabadi proposed a seizure prediction technique based on chaos theory and non-linear dynamics to create a return map depending on zero crossings [80]. This method consists of nine steps: raw EEG data recording from six channels, baseline noise reduction through filtering, signal segmentation to non-overlapping 5-min sections, PCA decomposition of the signal, zero-crossing rate estimation for the first PCA component, resampling of the second component based on the estimated zero-crossing rate, creation of a series of samples to construct a Poincare map, feature extraction, and finally estimation of the seizure risk. They evaluated this method with iEEG data from six patients of Freiburg database with 256-Hz sampling rate, 50-min pre-ictal, and 24 h of non-seizure data. Their method achieved a 20 ± 5 -min prediction time, an 86.6% sensitivity, and a 0.067/h false-alarm rate.

Williamson et al. presented a seizure prediction method that is based on estimating eigenspectral features from space-delay correlation and covariance matrices of EEG signal blocks with multiple delay scales [81]. An SVM classifier has been used in this method. An averaging process over 15-min windows is used as a post-processing step to get the final prediction score. This method was tested on the recordings of 19 patients from the Freiburg database having at least three seizures. It succeeded in predicting 71 out of 83 seizures. The false prediction rate was 13.8/h.

2 Conclusions

Table 1 shows a comparison between the different seizure detection and prediction methods. It is clear from this table that most seizure detection and prediction methods adopt time- or wavelet-domain features. For wavelet-domain method, several papers have adopted five-level decomposition for robust feature extraction. Few methods have used hybrid features like time and wavelet-domain features and achieved better performance than using features from one domain only. It is clear also that the EMD is a promising trend for seizure detection and prediction that needs further investigation. Also, we can say that seizure detection and prediction methods based on classifiers are better in performance than methods that do not implement classifiers. Multi-

Table 1 Summary of seizure detection and prediction methods

Method	Domain and algorithm classification	Single or multi-channel	Database	Frame length	Features	Classifier	Performance metrics	Hardware implementation
Runarsson and Sigurdsson [9]	Time, detection	Single channel	Self-recorded data	Variable length frames	Histogram bin amplitudes for amplitude difference and separation time between peaks and minima	SVM	Sensitivity: 90%	No
Yoo et al. [14]	Time, detection	Multi-channel	MIT database (scalp EEG)	2 s	Energies of sub-bands	SVM	Accuracy: 84.4%, classification energy 2.03 μ J	Yes
Dalton et al. [16]	Time, detection	Single channel	Dataset of 21 seizures	12 to 25 s	Signature of seizure	Template matching	Sensitivity: 91 %, specificity: 84 %, battery lifetime: 10.5 h	Yes
Zandi et al. [17,18]	Time, prediction	Multi-channel	561 h of scalp EEG with 86 seizures for 20 patients	15 s	Combined index	Non-linear SVM with Gaussian classifier	Sensitivity: 88.34%, false prediction rate: 0.155 h^{-1} , average prediction time: 22.5 min	No
Aarabi and He [19]	Time, prediction	Single channel	316 h of iEEG data containing 49 seizures for 11 patients from Freiburg database	10 s	Correlation dimension, correlation entropy, noise level, Lempel-Ziv complexity, largest Lyapunov exponent	No classifier	Average sensitivity: 79.9%, 90.2% with average false prediction rate: 0.17 and 0.11/h	No
Schelter et al. [25]	Time, prediction	Single channel	Eight patients with focal epilepsy	30 s	Probabilistic threshold	No classifier	Sensitivity: 60%	No
Wang et al. [26]	Time, prediction	Single channel	Data for five patients	10 min	Area under the ROC curve	KNN	Average accuracy: 70%	No
Bedeeuzzaman et al. [27]	Time, prediction	Single channel	21 patients from Freiburg database (scalp and iEEG)	1 min	MAD, IQR	Binary linear classifier	Sensitivity: 100%, FPR: 0 (for 12 patients), average prediction time: 51 to 96 min	No
Li et al. [28]	Time, prediction	Multi channel	21 patients from Freiburg database (scalp and iEEG)	5 s	Spike rate	No classifier	Accuracy: 75.8%, false prediction rate: 0.09	No
Chisci et al. [30]	Time, prediction	Multi channel	21 patients from Freiburg database (scalp and iEEG)	2 s	AR coefficients	SVM	Sensitivity: 100%, average prediction time: 60 min	No
Rana et al. [32]	Frequency, detection	Multi-channel	EEG and ECoG time series, BW: 0.5 to 100 Hz	10 to 60 s	Phase slope index	No classifier	Detection accuracy: 100%	No
Khamis et al. [33]	Frequency, detection	Single channel	12 patients with six data records (R1 to R6)	32 s	Range of frequencies, range of frequencies used for background subtraction, number of points, hemisphere parameters, moment parameters, artifact removal parameters, p -norm power, cutoff point	Powell's direction set method	Sensitivity: 91%, false positives per hour: 0.02	No
Acharya et al. [34]	Frequency, detection	Single channel	Self-recorded data	23.6 s	Phase entropy 1 (S_1), phase entropy 2 (S_2), approximate entropy (ApEn), and sample entropy (SampEn)	SVM, FSC, PNN, KNN, NBC, DT, and GMM	Average accuracy: 98.1%	No

Table 1 Summary of seizure detection and prediction methods (Continued)

Zhou et al. [12]	Wavelet, detection	Multi-channel	Freiburg database of 21 patients; six channels: channels 1, 2, and 3 near the epileptic focus, and channels 4, 5, and 6 in remote locations	4 s without overlapping	Lacunarity and fluctuation index on wavelet scales	Bayesian linear discriminant analysis (BLDA) classifier	Sensitivity: 96.25%, false detection rate: 0.13/h, mean delay time: 13.8 s	No
Liu et al. [36]	Wavelet, detection	Multi-channel	Dataset of 509 h from 21 epileptic patients	4 s	Relative energy, relative amplitude, coefficient of variation, fluctuation index	SVM	Sensitivity: 94.46%, specificity: 95.26%, false detection rate: 0.58/h	No
Panda et al. [37]	Wavelet, detection	Single channel	500 epochs of EEG data from five different brain activities (100 signals per epoch)	0.5 s	Energy, entropy, standard deviation	SVM	Accuracy: 91.2%	No
Khan et al. [38]	Wavelet, detection	Single channel	Self-recorded data for five patients	25 s	Energy and normalized coefficient of variation	Simple LDA classifier	Sensitivity: 83%, specificity: 100%, accuracy: 92%, overall precision: 87%	No
Wang et al. [56]	Wavelet, detection	Single channel	Changhai Hospital database (scalp EEG)	70 to 200 ms	Approximate entropy	Neyman-Pearson criteria and SVM	Detection accuracy: 98%, false detection rate: 6%	No
Zainuddin et al. [40]	Wavelet, detection	Single channel	University of Bonn database (scalp EEG)	23.6 s	Maximum, minimum, standard deviation of absolute wavelet coefficients	WNN	Sensitivity: 98%, accuracy: 98%	No
Niknazar et al. [42]	Wavelet, detection	Single channel	100 single-channel segments from Bonn University Database (scalp EEG)	23.6 s	Time delay, embedding dimension	ECOG	Accuracy: 98.67%	No
Daou and Labeau [43]	Wavelet, detection	Multi-channel	Nine patients from MIT database, and nine patients from Montreal Neurological Institute database (scalp EEG)	1 s	SPIHT codes	No classifier	Accuracy: 90%	No
Mehta et al. [44]	Wavelet, detection	Single channel	Self-recorded	10 s	Slope of the regression line on a logarithmic plot for the wavelet scales 6 to 2	No classifier	Slope decreases with onset	No
Shoab et al. [45]	Wavelet, detection	Multi-channel	MIT database (scalp EEG)	2 s	Wavelet energy	SVM	Sensitivity: 91% to 96%, latency: 4.7 to 5.3 s, false-alarm rate: 0.17 to 0.3/h	Yes
Zandi et al. [46]	Wavelet, detection	Multi-channel	EEG recordings from 14 patients approximately 75.8 h with 63 seizures	10 to 40 s	Combined seizure index	No classifier	Sensitivity: 90.5%, false detection rate: 0.51 h^{-1} , median detection delay: 7 s	No
Paul et al. [47]	Wavelet, prediction	Single channel	Data for rats	5 s	RSWE	No classifier	Detection: 90%	No
Hung et al. [48]	Wavelet, prediction	Multi-channel	11 patients from Freiburg database (scalp and iEEG)	1 h	Chaos features, wavelet features, correlation dimension	No classifier	Accuracy: 87%, false prediction rate: 0.24/h, average warning time: 27 min ahead the ictal	Yes

Table 1 Summary of seizure detection and prediction methods (Continued)

Chiang et al. [49]	Wavelet, prediction	Single channel	Freiburg database, CHB-MIT database (eight patients), National Taiwan University Hospital database (one patient)	60 s	Wavelet coherence	SVM	74.2% and 52.2% sensitivity on intracranial and scalp databases, sensitivity improvement by 29.0% and 17.4% for both databases	No
Rojas et al. [52]	Wavelet, prediction	Single channel	20 patients (267 seizures, 3,400 h)	Up to 22 h	Cross-frequency coupling	No classifier	Sensitivity: 100%	No
Gadhoumi et al. [54]	Wavelet, prediction	Multi-channel	1,565 h iEEG, 17 patients with mesial temporal lobe epilepsy with 175 seizures	1 min with 75% overlap	Distance, inclusion, persistence	SVM	Sensitivity: >85%, warning rate: < 0.35/h, proportion of time under warning: <30%	No
Gadhoumi et al. [55]	Wavelet, prediction	Multi-channel	Self-recorded dataset for six patients	2 s, disjoint	Wavelet energy and entropy	Binary classifier	Average sensitivity: >80%, FP rate: from 0.09 to 0.7 FP/h	No
Wang et al. [56]	Wavelet, prediction	Multi-channel	Ten patients (self-recorded data)	10 min with 50% overlap	Lyapunov exponent, correlation dimension, Hurst exponent, entropy	KNN	Sensitivity: 73%, specificity: 67%	No
Soleimani et al. [57]	Wavelet and time, prediction	Single channel	21 patients Freiburg database (scalp and iEEG)	10 s	Time- and wavelet-domain features	Neuro-fuzzy	Prediction: 99.52%, FPR: 0.1417/h	No
Moghim and Corne [59]	Wavelet and time, prediction	Single channel	One patient from Freiburg database (135 min, three seizures, 10 min following each seizure) (scalp and iEEG)	Up to 5 min	Time-domain energies, wavelet-domain energies, correlation dimension, max Lyapunov exponent	MC-SVM and EANN	Sensitivity and specificity with different values according to simulation assumptions	No
Tafreshi et al. [61]	EMD, detection	Single channel	Five patients of Freiburg database (scalp and iEEG)	4 to 6 s	Mean of the absolute of each IMF, wavelet features	Neural network	Accuracy: 95%	No
Orosco et al. [62]	EMD, detection	Single channel	90 EEG segments acquired for nine patients	1 h	Energies of the IMFs	No classifier	Sensitivity: 56%, specificity: 75%, positive predictive value: 61%, negative predictive value: 72%	No
Guarnizo and Delgado [63]	EMD, detection	Single channel	Five groups with 100 single-channel registers sampled at 173.61 Hz	Whole signal	Instantaneous frequency, amplitude of each EMD component, skewness, kurtosis, Shannon's entropy	Linear Bayes classifier	Accuracy: 98%	No
Alam and Bhuiyan [67,68]	EMD, detection	Single channel	Bonn University database (scalp EEG)	23.6 s	Skewness, kurtosis, variance, largest Lyapunov exponent, correlation dimension, approximate entropy from intrinsic modes	ANN	Accuracy: 100%	No
Bajaj and Pachori [69]	EMD, detection	Single channel	Freiburg database for 21 patients (scalp and iEEG)	15 s	Modified central tendency measure	No classifier	Sensitivity: 90%, specificity: 89.31%, error detection rate: 24.25%	No
Qi et al. [71]	EMD, prediction	Single channel	Pre-surgical epilepsy monitoring database with 80.4 h of EEG data with ten seizures of four patients	Whole signal	IMF-VoE	No classifier	Sensitivity: 100%, false detection rate: 0.16/h, average time delay: 10.7 to 19.4 s are 19.4 s	No
Vanrumste et al. [74]	SVD, detection	Single channel	Simulated EEG signals	10 s	Dipole parameters, relative residual energy (RRE)	No classifier	Visual inspection of parameters	No

Table 1 Summary of seizure detection and prediction methods (Continued)

Shahid et al. [76]	SVD, detection	Single channel	Recordings of four pediatric patients with 20 seizures	1 s	Largest r -singular values, Euclidean distance from the r -singular values of a baseline window located 1 h before the seizure	No classifier	Visual inspection of results	No
Xie and Krishnan [79]	PCA in wavelet domain, detection	Single channel	Data for eight patients	4,097 s	Adjusted random index (ARI)	Empirical classifier	ARI up to 1	No
Miri and Nasrabadi [80]	PCA, prediction	Multi-channel	Six patients of Freiburg database (scalp and iEEG)	5 min	Zero-crossing rate, a statistical index	No classifier	Prediction time: 20 ± 5 min, sensitivity 86.6%, false-alarm rate: 0.067%	No
Williamson et al. [81]	PCA, FFT, prediction	Multi-channel	Freiburg database (scalp and iEEG)	15 s	Eigen spectral features	SVM	Sensitivity: 85.5%, false prediction rate: 0.033/h	No

channel techniques are also more superior in performance than single-channel techniques.

Competing interests

The authors declare that they have no competing interests.

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