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Automated Epileptic Seizure Detection Methods: A Review Study

Alexandros T. Tzallas, Markos G. Tsipouras,
Dimitrios G. Tsalikakis, Evaggelos C. Karvounis,
Loukas Astrakas, Spiros Konitsiotis and Margaret Tzaphlidou
*Department of Medical Physics, Medical School, University of Ioannina, Ioannina,
Greece*

1. Introduction

Epilepsy is a neurological disorder with prevalence of about 1-2% of the world's population (Mormann, Andrzejak, Elger & Lehnertz, 2007). It is characterized by sudden recurrent and transient disturbances of perception or behaviour resulting from excessive synchronization of cortical neuronal networks; it is a neurological condition in which an individual experiences chronic abnormal bursts of electrical discharges in the brain. The hallmark of epilepsy is recurrent seizures termed "**epileptic seizures**". Epileptic seizures are divided by their clinical manifestation into partial or focal, generalized, unilateral and unclassified seizures (James, 1997; Tzallas, Tsipouras & Fotiadis, 2007a, 2009). Focal epileptic seizures involve only part of cerebral hemisphere and produce symptoms in corresponding parts of the body or in some related mental functions. Generalized epileptic seizures involve the entire brain and produce bilateral motor symptoms usually with loss of consciousness. Both types of epileptic seizures can occur at all ages. Generalized epileptic seizures can be subdivided into absence (petit mal) and tonic-clonic (grand mal) seizures (James, 1997).

Monitoring brain activity through the electroencephalogram (EEG) has become an important tool in the diagnosis of epilepsy. The EEG recordings of patients suffering from epilepsy show two categories of abnormal activity: **inter-ictal**, abnormal signals recorded between epileptic seizures; and **ictal**, the activity recorded during an epileptic seizure (Fig. 1). The EEG signature of an inter-ictal activity is occasional transient waveforms, as either isolated spikes, spike trains, sharp waves or spike-wave complexes. EEG signature of an epileptic seizure (ictal period) is composed of a continuous discharge of polymorphic waveforms of variable amplitude and frequency, spike and sharp wave complexes, rhythmic hypersynchrony, or electrocerebral inactivity observed over a duration longer than the average duration of these abnormalities during inter-ictal periods (McGrogan, 2001).

Given that ictal recordings (recording during an epileptic seizure) are rarely obtained, EEG analysis of patients suffering from epilepsy usually relies on inter-ictal findings. In those inter-ictal EEG recordings, epileptic seizures are usually activated with photo stimulation, hyperventilation and other methods (McGrogan, 2001). However, one weakness of these

stimulation techniques is that provoked epileptic seizures do not necessarily have the same behaviour as the spontaneous ones. The introduction of long-term video-EEG recordings has been an important milestone providing not only the possibility to capture and analyze ictal events, but also contributing to valuable clinical information, especially in those candidates evaluated for epilepsy surgery. Prior to the advent of portable recording devices all EEG recording took place in special hospital units. The introduction of portable recording systems (ambulatory EEG), however, has allowed outpatient EEG recording to become more common. This method has advantages that patients are recorded in their normal environment without the reduction in seizure frequency usually seen during a long (and expensive) in-patient sessions. Many studies have shown that ambulatory EEG recordings generally increase the yield of useful diagnostic information and improve the overall medical management of patients (Casson, Yates, Smith, Duncan, & Rodriguez-Villegas, 2010; Waterhouse, 2003).

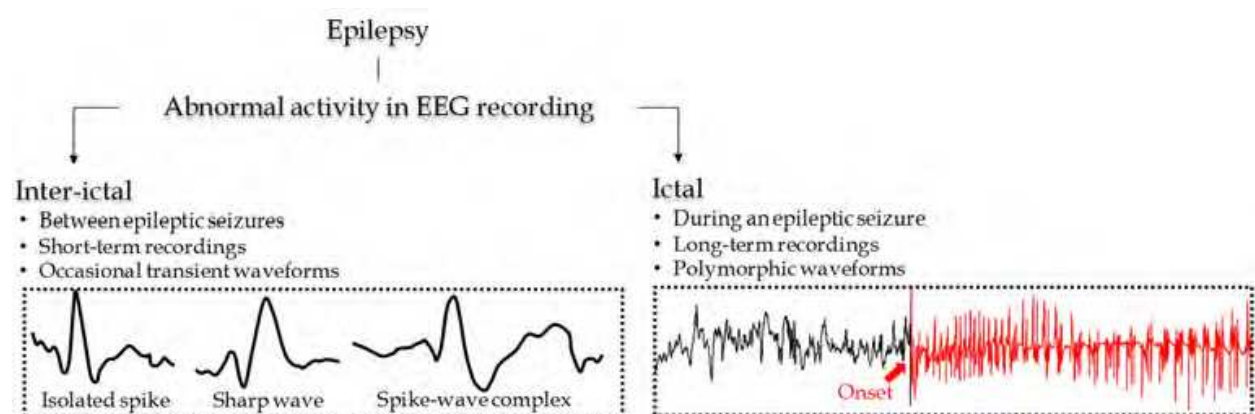


Fig. 1. During inter-ictal periods, or between epileptic seizures, EEG recordings of patients affected by epilepsy will exhibit abnormalities like isolated spike, sharp waves and spike-wave complexes (usually all termed as inter-ictal spikes or spikes). In ictal periods, or during epileptic seizures, the EEG recording is composed of a continuous discharge of one of these abnormalities, but extended over a longer duration and typically accompanied by a clinical correlate (Exarchos, Tzallas, Fotiadis, Konitsiotis & Giannopoulos, 2006; Oikonomou, Tzallas & Fotiadis, 2007; Tzallas et al., 2006; Tzallas, Oikonomou, & Fotiadis, 2006; Tzallas, et al., 2007a; Tzallas, Tsipouras & Fotiadis, 2007b; Tzallas, et al., 2009).

Generally, the detection of epilepsy can be achieved by visual scanning of EEG recordings for inter-ictal and ictal activities by an experienced neurophysiologist. However, visual review of the vast amount of EEG data has serious drawbacks. Visual inspection is very time consuming and inefficient, especially in the case of long-term recordings. In addition, disagreement among the neurophysiologists on the same recording is possible due to the subjective nature of the analysis and due to the variety of inter-ictal spikes morphology. Moreover, the EEG patterns that characterize an epileptic seizure are similar to waves that are part of the background noise and to artefacts (especially in extracranial recordings) such as eye blinks and other eye movements, muscle activity, electrocardiogram, electrode "pop" and electrical interference. For these reasons, methods for the automated detection of inter-ictal spikes and epileptic seizures can serve as valuable clinical tools for the scrutiny of EEG data in a more objective and computationally efficient manner.

2. Automated analysis of epileptic EEG recordings

Automated analysis of EEG recordings for assisting in the diagnosis of epilepsy started in the early 1970s (Gotman, 1999; Tzallas, et al., 2007a, 2007b, 2009; Wilson & Emerson, 2002). From the beginning, the automated analysis of epileptic EEG recordings has progressed in two main directions:

- inter-ictal spike detection or spike detection analysis, and
- epileptic seizure analysis.

2.1 Automated spike detection analysis

The automatic spike detection problem can be simply transferred to the detection of the presence of inter-ictal spikes in the multichannel EEG recording with high sensitivity and selectivity (James, 1997; Oikonomou, et al., 2007). That means that high proportion of true events must be detected with a minimum number of false detections. Although desirable, it is not realistic to expect high sensitivity and selectivity due to the imprecise definition among neurophysiologists of what constitutes a spike varies. Several studies evaluated this issue by extracting features from the raw EEG recordings that best describe the spike morphology. On the other hand, other studies have chosen to use machine learning techniques (usually artificial neural networks) as a means of using the raw EEG without having to make any decision concerning what parameters are more important than others in detecting spikes (James, 1997). Whatever the method used, the spike detection problem seems to be divided into two main stages: feature extraction and classification (Fig. 2).

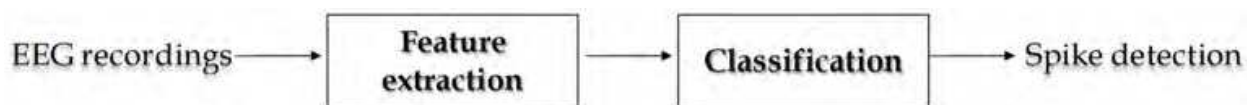


Fig. 2. The spike detection problem seems to be broken down into two main stages: feature extraction and classification. This can be viewed as mapping the N -dimensional EEG pattern space to a F -dimensional feature space (where $N \geq F$) and then performing classification in the feature space. In the case of use of raw EEG recordings without feature extraction, this can be seen as the case where the N -dimensional EEG space is mapped onto an identical N -dimensional feature space where classification then takes place (James, 1997).

It is well established that, apart from the spike detection on a single channel itself, other contextual information (spatial and temporal) is also vital to neurophysiologists when identifying candidate transient waveforms as spikes (James, Jones, Bones, & Carroll, 1999; Tzallas, Karvelis, et al., 2006). This information is related to other channels waveforms that take place at the same time. Based on the above, the spike detection problem depicted in Fig. 2, can now be modified, as shown in Fig. 3, to incorporate the use of spatio-temporal information in helping detect spikes in the multichannel EEG recordings.

The following provides a short summary of the most common methods to the spike detection problem in the literature (Gotman, 1999; Wilson & Emerson, 2002). These methods have been grouped according to their spike detection criterion into nine (9) categories:

- methods based on traditional recognition techniques, known as **mimetic** techniques,
- methods based on **morphological** analysis,

- c. methods using **template matching** algorithms,
- d. methods based on **parametric** approaches
- e. methods based on **independent component** analysis
- f. methods based on **artificial neural networks**,
- g. methods based on **clustering** techniques,
- h. methods employed **data mining** and **other classification techniques**, and
- i. methods utilizing **knowledge-based rules**.

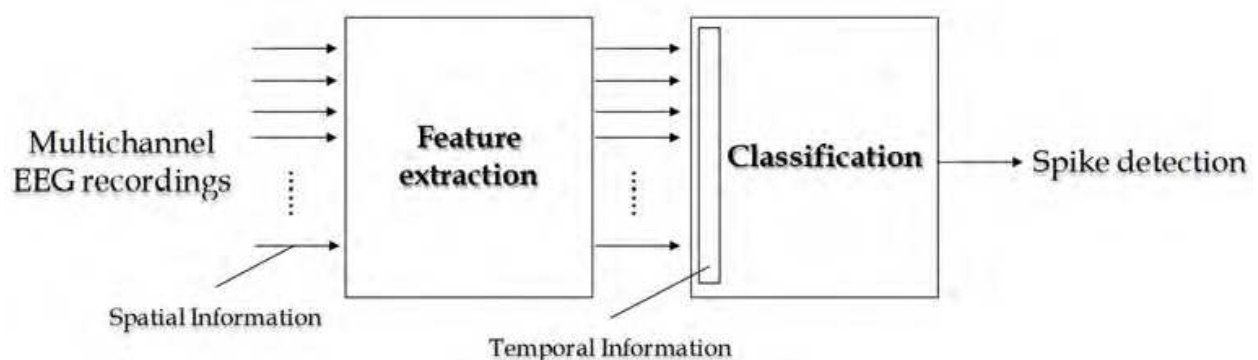


Fig. 3. The spatial and temporal information (contextual) is important in the spike detection problem. The N -dimensional EEG pattern space is mapped onto a F -dimensional feature space for each channel in the EEG recording. The multichannel features introduce spatial information into the method. The classification of candidate spikes then takes place using features extracted from the pattern space. Temporal information can then be introduced to the classification process by considering the presence of previous spikes in the EEG throughout the multichannel recording and allowing this to strengthen or weaken the outcome due to spatial information alone (James, 1997).

- a. Methods based on traditional recognition techniques, known as mimetic techniques

Mimetic methods are based on the hypothesis that the process of identifying a transient waveform in EEG recordings as spike could be divided into well-defined steps representing the reasons and expertise of a neurophysiologist (Gotman, 1982; Gotman & Gloor, 1976; Guedes de Oliveira, 1983; Ktonas, 1983; Ktonas, Luoh, Kejariwal, Reilly, & Seward, 1981). Distinctive attributes of the spikes such as slope, height, duration and sharpness are compared with values provided by the neurophysiologists. Gotman and Gloor (1976) decomposed the waveform into two half-waves with opposite directions. Similar methods for decomposing the EEG waveform into half-waves have been used by many authors (Davey, Fright, Carroll, & Jones, 1989; Faure, 1985; Webber, Litt, Wilson, & Lesser, 1994). Faure (1985) introduced a concept where the duration, amplitude, and slope attributes of half-waves were used to classify them into states.

- b. Methods based on morphological analysis

Methods based on morphological analysis characterize the waveforms, frequency bands, or time-frequency representations of spikes (Gotman, 1990, 2003; Michel, Seeck, & Landis, 1999). Morphological analysis has proven an efficient tool in EEG signal processing since it can decompose raw EEG signal into several physical parts. Background activity and spike component are separated and the main morphological characteristic of spikes is retained.

Pon and coworkers (2002) selected a circle structure element and utilized mathematical morphology and wavelet transform to detect bi-directional spikes in epileptic EEG recordings. Nishida and coauthors (1999) presented a detection method based on morphological filter, in which open-closing operation was selected as the basic algorithm and the general structure elements are designed by second-order polynomial functions. Using a morphological filter with proper morphological operation and structure elements, it was possible to restrain the background activity completely. Xu and coworkers (2007) presented a method for automatic spike detection by using an improved morphological filter. The basic idea of the improved morphological filter was to separate spikes and its background activity by the differences of their geometric characteristics.

c. Methods using template matching algorithms,

In the template matching algorithms, the user manually selects spikes from a set of test EEG recordings that are averaged to create a template (El-Gohary, McNames, & Elsas, 2008; Lopes da Silva, A., & H., 1975; Sankar & Natour, 1992). Many researchers (Goelz, Jones, & Bones, 2000; Schiff, Aldroubi, Unser, & Sato, 1994; Senhadji, Dillenseger, Wendling, Rocha, & Kinie, 1995; Senhadji & Wendling, 2002) used wavelets to obtain features of the signal for template building and spike detection.

d. Methods based on parametric approaches

In the parametric approaches, researchers (Birkemeier, Fontaine, Celesia, & Ma, 1978; Diambra & Malta, 1999; Lopes da Silva, et al., 1975) assume local stationarity of the noise and spikes are detected as deviation from that stationarity. Tzallas and coauthors (2006) presented a new technique based on a time-varying autoregressive model that made use of the nonstationarities of EEG. The autoregressive parameters were estimated via Kalman filter. The signal was first processed to accentuate the spikes and attenuate background activity and then passed through a thresholding function to determine spikes locations.

e. Methods based on independent component analysis

Various spike detection approaches based on independent component analysis (ICA) have been proposed in applications to EEG recordings (Hesse & James, 2007; Ossadtchi et al., 2004). Kobayashi and coauthors (1999) performed both model based and real data demonstrations of the use of ICA to isolate spikes from multichannel EEG data (Ossadtchi, et al., 2004). In this approach, ICA is applied to spatio-temporal data and components resembling abnormal epileptic activities selected by visual inspection and then interpreted by a neurophysiologist (Hesse & James, 2007; Ossadtchi, et al., 2004). Kobayashi and coworkers (2002) used ICA decomposition together with the RAP-MUSIC source localization approach (Mosher, Baillet, & Leahy, 1999; Mosher & Leahy, 1998; Mosher, Leahy, & Lewis, 1999) to detect potentially epileptogenic regions (Ossadtchi, et al., 2004). Rather than fitting a dipole to each independent component separately (Zhukov, Weinstein, & Johnson, 2000), Kobayashi and coauthors (2002) followed a multidimensional ICA paradigm and defined an inter-ictal subspace spanned by the columns of the estimated mixing matrix visually identified as corresponding to epileptic components (Ossadtchi, et al., 2004).

f. Methods based on artificial neural networks

In the sixth category belong approaches built upon artificial neural networks (ANNs) which simulate the behavior of a collection of neurons (Tzallas, Karvelis, et al., 2006). ANNs have

been trained using either raw data (Ko & Chung, 2000; Ozdamar & Kalayci, 1998; Pang, Upton, Shine, & Kamath, 2003; Webber, et al., 1994) or select features (Acir, Oztura, Kuntalp, Baklan, & Guzelis, 2005; Castellaro et al., 2002; Gabor & Seyal, 1992; Liu, Zhang, & Yang, 2002; Pang, et al., 2003; Tzallas, Karvelis, et al., 2006; Webber, et al., 1994) to detect spikes. In the first case, windows of raw EEG data are fed into an ANN. In the second case, two types of features are used: (1) waveforms features such as duration, slope, sharpness, and amplitude, which are extracted from spikes and (2) context features, such as EEG variance and baseline crossings, which are extracted from the EEG activity surrounding the spikes.

g. Methods based on clustering techniques

Clustering techniques in the field of automated spike detection analysis has also been addressed. Hierarchical agglomerative methods and self organizing maps have been used for clustering EEG segments (Sommer & Golz, 2001). The nearest mean (NM) algorithm (Wahlberg & Salomonsson, 1996), the ant *K*-mean algorithm (Shen, Kuo, & Hsin, 2009) and the fuzzy *C*-means (FCM) algorithm (Inan & Kuntalp, 2007; Wahlberg & Lantz, 2000) have been employed in order to cluster spikes. In addition, the *K*-means algorithm has been used in order to cluster spikes and other types of transient waveforms (Exarchos, et al., 2006; Tzallas, Karvelis, et al., 2006).

h. Methods employed data mining and other classification techniques

Data mining (DM) techniques are also used to build automatic spike detection models, (Exarchos, et al., 2006; Valenti et al., 2006). In DM, the identification of spikes does not need a clear definition of spike morphology. In addition, other classification schemes such as support vector machines (SVMs) have also been applied to spike detection (Acir & Guzelis, 2004; Acir, et al., 2005; Tzallas et al., 2005). The main idea was to adjust the position of the separator (line, plane, hyperplane) between spike and non-spike patterns based on the distance from misclassified outliers.

i. Methods utilizing knowledge-based rules

The majority of the methods, mainly those belonging to the first four categories (mimetic, morphological, template matching and parametric) deals with the single EEG channel data only. Knowledge-based reasoning in addition to the aforementioned methods is widely used (Tzallas, Karvelis, et al., 2006). This arises from the need to incorporate knowledge of neurophysiologists that adopt spatial and temporal rules (Acir, et al., 2005; Dingle, Jones, Carroll, & Fright, 1993; Edwards, James, Coakley, & Brown, 1976; Glover, Raghavan, Ktonas, & Frost, 1989; James, 1997; James, et al., 1999; Liu, et al., 2002; Ozdamar, Yaylali, Jayakar, & Lopez, 1991; Tzallas, Karvelis, et al., 2006; Webber, et al., 1994). More specifically, Glover and coauthors (1989), Dingle and coauthors (1993), and Liu and coauthors (2002) used a knowledge-based system with a high degree of success, taking advantage of both spatial and temporal information. Ozdamar and his coworkers (1991) made use of spatial information by integrating the outputs of individual channel spike detection ANNs, from four channels into a single ANN module trained to recognize the common spatial distributions of spikes. Webber and coauthors (1994) used four channels simultaneously, while including spatial contextual information of a 1 sec long window around the spike, in the training of their ANN. James and coworkers (1999) have employed a spatial-combiner stage with the outputs of a self-organizing ANN, using a fuzzy logic approach, in order to

incorporate spatial information in the multichannel EEG recordings. In a similar way, Acir and coauthors (2005) and Tzallas and coauthors (2006), in the final stage of their spike detection method, combined the outputs of the classification stage (ANN or SVM) in such a way as to confirm the presence of spike across two or more channels of the EEG recordings.

Based on the foregoing, it is apparent that when deciding on a method capable of the detection of spikes in the multichannel EEG recordings, a few number of important questions need to be answered. Fig.4 illustrates the questions and some of the possible answers (James, 1997). To sum up, these are:

- Should raw EEG recordings be used for the classification or should features be extracted first and the classification performed in the new feature space?
- If features are to be extracted, what features adequately describe spikes for the classification purposes?
- Once the decision made on raw vs. features, which machine learning algorithm should be used?

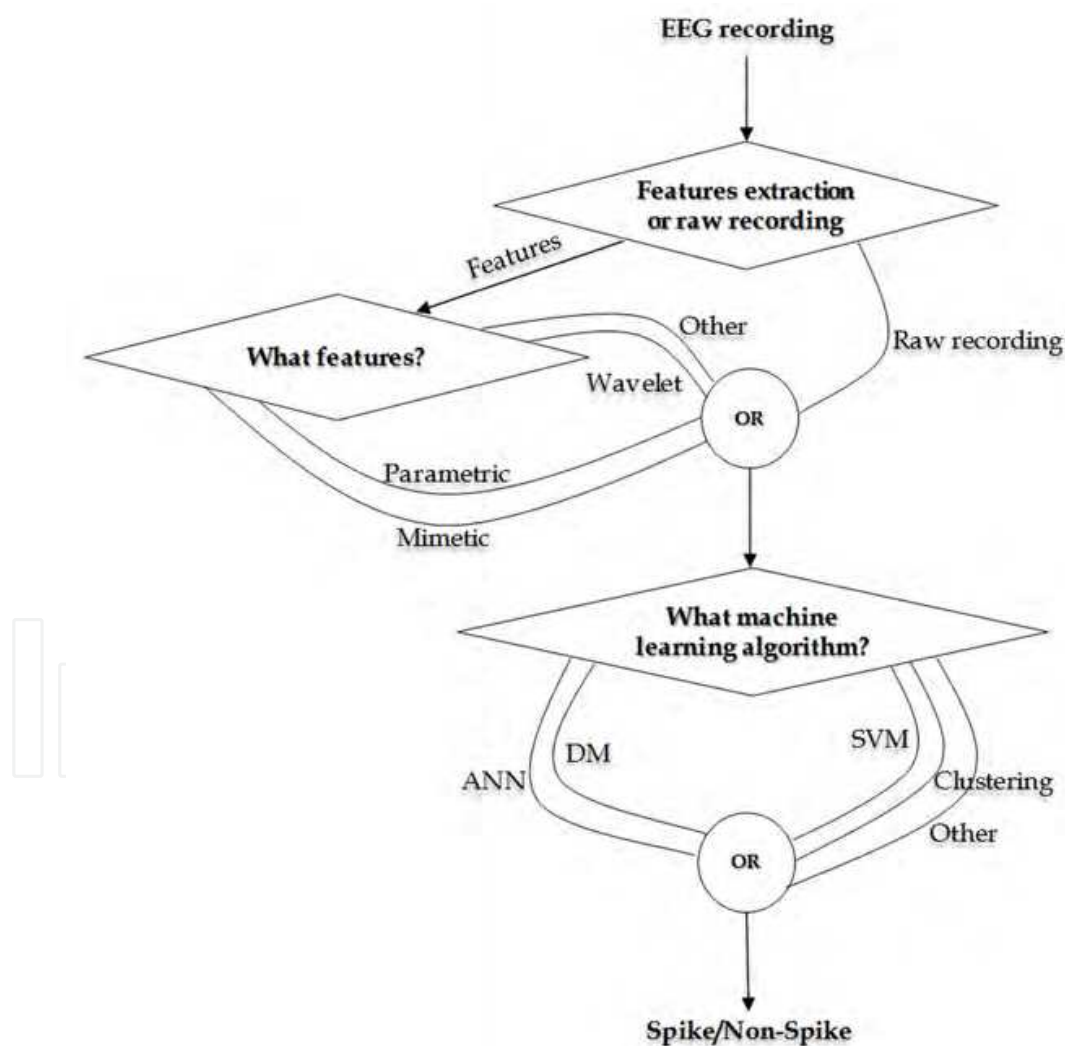


Fig. 4. Questions to be answered in choosing the best spike detection criterion. Once the method for spike detection has been established, it is important to keep in mind the need to incorporate spatial and temporal information (James, 1997).

2.1.1 Spike enhancement before spike detection analysis

From the preceding discussion, in the spike detection problem, a balance must be obtained between having high sensitivity and high selectivity. It is relatively easy to adjust method parameters to obtain performance where all spikes are found in a given patient, but this would usually be accompanied by an unacceptably large number of false detections (James, 1997; James, Hagan, Jones, Bones, & Carroll, 1997; Oikonomou, et al., 2007). Alternatively, it is relatively easy to have a method with very low false detection rates, but this would be accompanied by an unacceptably large number of missed events. Many researchers argue that it is better to have a high sensitivity, to minimize missed events, and to have more false detections that can be checked by a neurophysiologist, rather than missing the events altogether (James, 1997; Oikonomou, et al., 2007). If we look at the method from the point of view of minimizing the number of false detections then the number of missed events will increase. However, if spikes can be enhanced prior to the use of a spike detection criterion, it should be possible to increase the sensitivity minimizing missed events, while maintaining the selectivity at a satisfactory level. Thus, a spike enhancement stage would not be a detection stage, but it would simply aim to enhance anything vaguely spike like, is needed. This means that actual spikes, as well as spike like artefacts and background will be enhanced, i.e. a large number of unwanted waveforms will be enhanced along with real spikes. This is quite acceptable as long as the spike detection method has high selectivity. To our knowledge, there few methods that explicitly addressed the spike enhancement problem in epileptic EEG recordings (James, et al., 1997; Lopes da Silva, et al., 1975; Oikonomou, et al., 2007). Lopes da Silva and co-authors (1975) used the method of modelling the background EEG with an autoregressive prediction filter and detecting transient waveforms by examining the prediction error. The autoregressive filter was calculated from a segment of the background EEG which is assumed to be stationary. James and coworkers (1997) made use of the multireference adaptive noise cancelling (MRANC) in which the background EEG on adjacent channels in the multichannel EEG recording is used to adaptively cancel the background EEG on the channel under investigation. Oikonomou and coauthors (2007) have presented a method for spike enhancement in EEG recordings, based on time-varying autoregressive model in order to take advantage of the nonstationarity nature of the EEG signal. More specifically, the method was based on the assumption that EEG consists of an underlying background activity, which was assumed stationary, and superimposed transient nonstationarities such spikes and artifacts. The method used a time-varying autoregressive model for the accentuation of spikes and other transient waveforms that are similar to spikes. The parameters of the model were estimated by Kalman filter.

After that, a complete spike detection scheme can be thought as a two-stage process: enhancement and detection (Fig. 5).

The purpose of the enhancement stage is to make the spike samples stand out from the rest of the data, thereby simplifying the subsequent task of detection. Depending on the nature of the enhancement strategy, several EEG spike detection schemes have been proposed categorized into three broad classes: (i) time domain techniques (Kim & Kim, 2000; Malarvili, Hassanpour, Mesbah, & Boashash, 2005; Mukhopadhyay & Ray, 1998) (ii) signal modeling approaches (Dandapat & Ray, 1997; James, et al., 1997; Tzallas, Oikonomou, et al., 2006), and (iii) transform domain methods (Durka, 2004; Hassanpour, Mesbah, & Boashash, 2004).

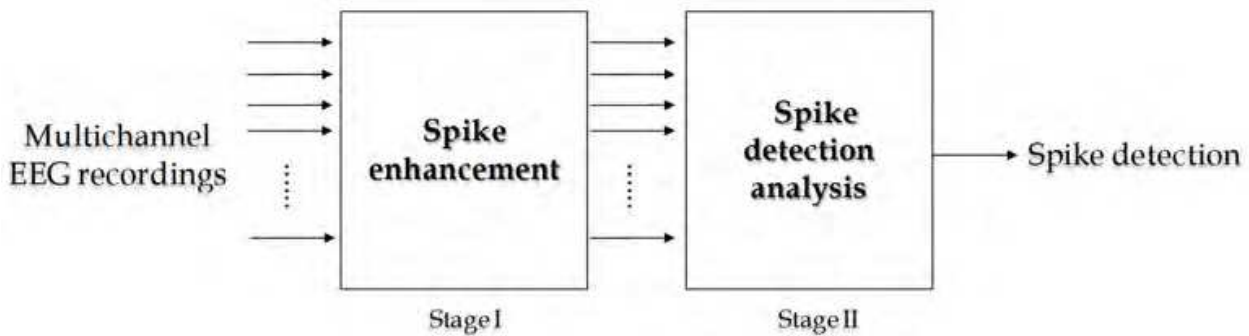


Fig. 5. Complete spike detection methods consists of two stages: (I) spike enhancement and (II) spike detection analysis. The spike enhancement stage processes an EEG recording by attenuating the background EEG, thus primarily leaving only transients waveforms -which are then classified as spikes or non-spikes by following stage II (spike detection analysis which is analytically described in the section 2.1). The main goal of the spike enhancement stage is to increase the sensitivity of the overall method to candidate spikes, while maximizing selectivity (minimizing the number of candidate spikes which are not epileptic passed onto the next stage) (Tzallas, Oikonomou, et al., 2006).

2.2 Automated epileptic seizure analysis

Automated epileptic seizure analysis (Fig. 6) refers collectively to methods for:

- epileptic seizures detection,
- epileptic seizures prediction, and
- epileptic seizures origin localization.

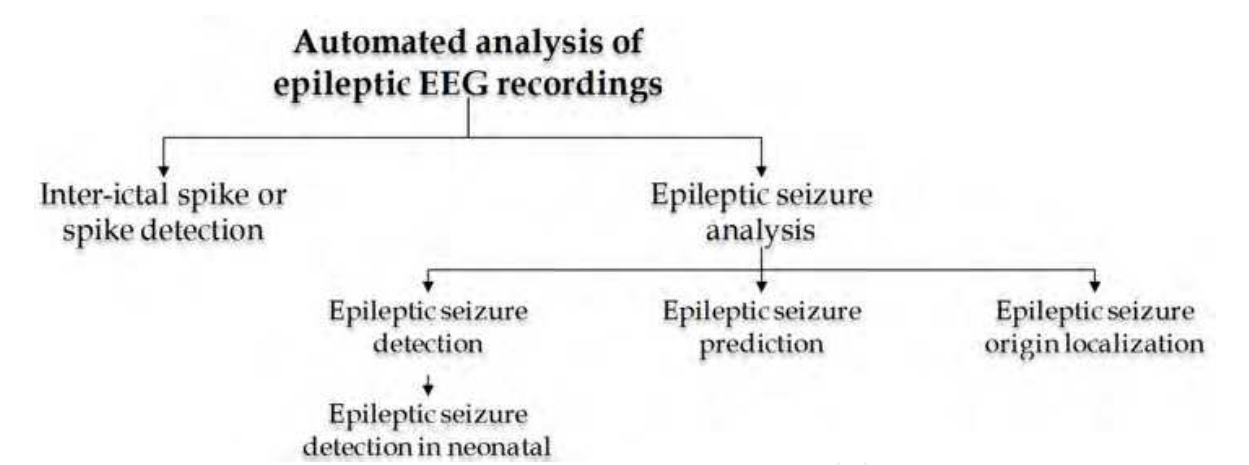


Fig. 6. Automated analysis of epileptic EEG recordings addresses two major problems: 1) inter-ictal spike detection or spike detection (section 2.1) and 2) epileptic seizure analysis. In addition, methods for automated epileptic seizure analysis can be divided into three categories: (i) epileptic seizure detection, (ii) epileptic seizure prediction, and (iii) epileptic seizure origin localization (Tzallas, et al., 2007a, 2007b, 2009).

In the literature, many algorithms for epileptic seizures detection have been proposed using classical signal processing methods (Gotman, 1999; McSharry, He, Smith, & Tarassenko, 2002). All suggested signal processing’s methods aim to detect various patterns in EEG recordings that are the manifestation of an epileptic seizure. The entire process of methods

developed for automated epileptic seizure detection can be generally subdivided into two main stages: (i) feature extraction, and (iii) classification (Fig. 7).

The selection of discriminative features is the basis of almost all epileptic seizure detection methods. Sometimes the choice for certain features is based on the physiological phenomena that need to be detected. Some authors referred to the fact that during an epileptic seizure many neurons fire synchronously (Gotman, 1999). To get a measure of this "synchronicity" they determined features such as the autocorrelation function (Liu, et al., 2002), the synchronization likelihood (Altenburg, Vermeulen, Strijers, Fetter, & Stam, 2003), or the nearest neighbour phase synchronization (van Putten, 2003). Other authors based their feature choice on morphological characteristics of epileptic EEG recordings. Epileptic seizures are often visible in EEG recordings as rhythmic discharges or multiple spikes. For spike detection, Gotman (1982) developed an algorithm that first breaks down the EEG signal into half-waves. Then morphological characteristics of these half-waves, such as amplitude and duration, were used to determine whether they are part of an epileptic seizure or not (Gotman, 1982, 1999).

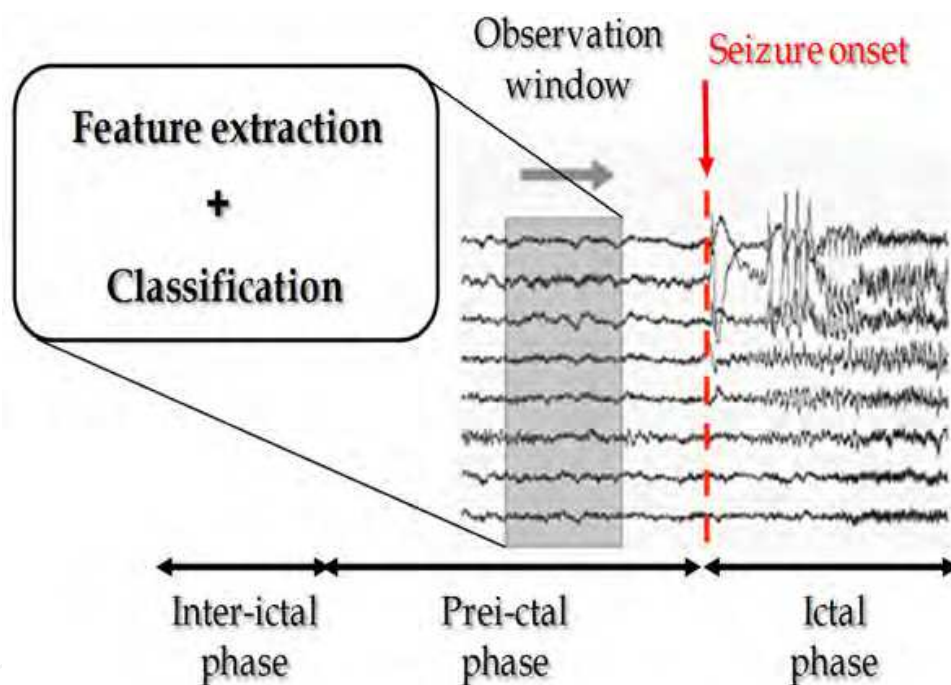


Fig. 7. Most of the automated epileptic seizure detection methods share certain common stages: (i) feature extraction and (ii) classification. By means of a moving-window analysis, features are calculated which is intended to characterise the multichannel EEG recordings. Then, the classification stage is employed to decide, from the calculated features, whether this EEG represents an epileptic seizure or not.

For rhythmic discharges, fast Fourier transform based (Polat & Gunes, 2007, 2008a, 2008b), frequency domain (Alkan, Koklukaya, & Subasi, 2005; Chua, Chandran, Acharya, & Lim, 2008; Gabor, 1998; Iscan, Dokur, & Tamer, 2011; Mousavi, Niknazar, & Vahdat, 2008; Murro et al., 1991; Nigam & Graupe, 2004; Sadati, Mohseni, & Magshoudi, 2006; Srinivasan, Eswaran, & Sriraam, 2005; Ubeyli, 2010a), time-frequency based (Martinez-Vargas, Avendano-Valencia, Giraldo, & Castellanos-Dominguez, 2011; Subasi & Gursoy, 2010; Tzallas, et al., 2007a, 2007b, 2009) or wavelet based features (Adeli, Ghosh-Dastidar, &

Dadmehr, 2007; Guler & Ubeyli, 2005, 2007; Guo, Rivero, Dorado, Rabunal, & Pazos, 2010; Guo, Rivero, & Pazos, 2010; Guo, Rivero, Seoane, & Pazos, 2009; Kiymik, Subasi, & Ozcalik, 2004; Lima, Coelho, & Eisencraft, 2010; H. Ocak, 2008; H. Ocak, 2009; Orhan, Hekim, & Ozer, 2011; Polat & Gunes, 2008b; Sadati, et al., 2006; Subasi, 2007a, 2007b; Subasi, Alkan, Koklukaya, & Kiymik, 2005; Subasi & Gursoy, 2010; Ubeyli, 2008c, 2009b, 2009c; Wang, Miao, & Xie, 2011) were often used. Some studies did not use prior information and just used large sets of various features. Aarabi and coauthors (2006) evaluated a large feature set containing various feature types. Their results showed that the most discriminative features for neonatal seizure detection¹ are morphological based features, such as amplitude, shape and duration of waveforms. In addition, time domain features such as statistical features (Adjouadi et al., 2005), Hjorth's descriptors (Hjorth, 1970), nonlinear features (Kannathal, Acharya, Lim, & Sadasivan, 2005; McSharry, et al., 2002)- correlation dimension (Elger & Lehnertz, 1998), Lyapunov exponent (Guler & Ubeyli, 2007; Guler, Ubeyli, & Guler, 2005; Ubeyli, 2006; Ubeyli, 2010b) and other features obtained from convolution kernels (Adjouadi et al., 2004), eigenvector methods (Naghsh-Nilchi & Aghashahi, 2010 ; Ubeyli, 2008a, 2008b, 2009a; Ubeyli & Guler, 2007), principal component analysis (PCA) (Ghosh-Dastidar, Adeli, & Dadmeh, 2008; Hesse & James, 2007; James & Hesse, 2005; Polat & Gunes, 2008a; Subasi & Gursoy, 2010), ICA (Hesse & James, 2007; James & Hesse, 2005; Subasi & Gursoy, 2010), crosscorrelation function (Chandaka, Chatterjee, & Munshi, 2009; Iscan, et al., 2011), and entropy (Guo, Rivero, Dorado, et al., 2010; Guo, Rivero, & Pazos, 2010; Kannathal, Acharya, et al., 2005; Kannathal, Choo, Acharya, & Sadasivan, 2005; Liang, Wang, & Chang, 2010; Naghsh-Nilchi & Aghashahi, 2010 ; H. Ocak, 2009; Srinivasan, Eswaran, & Sriraam, 2007; Wang, et al., 2011) have been proposed to characterize the EEG signal. It is also possible to select features using genetic programming (Firpi, Goodman, & Echauz, 2005; Guo, Rivero, Dorado, Munteanu, & Pazos, 2011). In this way, various features were extracted that were able to detect epileptic seizures, but these features did not have a physiological meaning.

Once a set of features has been obtained to characterise a section of EEG, it is necessary to apply a classification method in order to decide whether this section of EEG is taken from an epileptic seizure or not. Just as a wide variety of features has been used, an equally varied set of classification methods can be found in the literature. The classification methods varied from simple threshold (Altunay, Telatar, & Erogul, 2010; Martinez-Vargas, et al., 2011), rule based decisions (Gotman, 1990, 1999), or linear classifiers (Ghosh-Dastidar, Adeli, & Dadmeh, 2007; Iscan, et al., 2011; Liang, et al., 2010; Subasi & Gursoy, 2010) to ANNs (Ghosh-Dastidar, et al., 2007, 2008; Guler, et al., 2005; Mousavi, et al., 2008; Nigam & Graupe, 2004; Srinivasan, et al., 2005, 2007; Tzallas, et al., 2007a, 2007b, 2009; Ubeyli, 2006, 2009c; Ubeyli, 2010b) that have a complex shaped decision boundary. Other classification methods have been used using SVMs (Chandaka, et al., 2009; Guler & Ubeyli, 2007; Iscan, et al., 2011; Liang, et al., 2010; Lima, et al., 2010; Subasi & Gursoy, 2010; Ubeyli, 2008a; Ubeyli, 2010a), *k*-nearest neighbour classifiers (Guo, et al., 2011; Iscan, et al., 2011; Liang, et al., 2010; Orhan, et al., 2011; Tzallas, et al., 2009), quadratic analysis (Iscan, et al., 2011), logistic regression (Alkan, et al., 2005; Tzallas, et al., 2009), naive Bayes classifiers (Iscan, et al., 2011;

¹ The detection of epileptic seizures in neonates is quite different from that in adults: the discharges are often much slower (down to 0.5 Hz), epileptic seizure onset can be gradual and epileptic seizures can last several minutes, the waveforms of epileptic seizures and the inter-ictal background show a high level of variability.

Tzallas, et al., 2009), decision trees (Iskan, et al., 2011; Polat & Gunes, 2007; Tzallas, et al., 2009), Gaussian mixture model (Chua, et al., 2008; Lima & Coelho, 2011), mixture of expert model (Subasi, 2007b; Ubeyli, 2007, 2008c; Ubeyli & Guler, 2007) and adaptive neurofuzzy inference systems (Guler & Ubeyli, 2005; Kannathal, Choo, et al., 2005).

In addition to epileptic seizure detection methods, prediction methods have become increasingly valuable since detection of seizures at an early stage can warn a patient that a seizure is about to occur. Additionally, these methods can alert medical staff, and allow them to perform behavioural testing to further assess which specific functions may be impaired because of an epileptic seizure and help them in localizing the source of the epileptic seizure activity. Methods used to predict epileptic seizures include time-domain analysis (Lange, Lieb, Engel, & Crandall, 1983), frequency-based methods (Schiff et al., 2000), nonlinear dynamics and chaos (Lehnertz et al., 2001), methods of delays (Le Van Quyen et al., 2001), and intelligent approaches (Geva & Kerem, 1998). Advances in seizure prediction promise to give rise to implantable devices able to warn of impending seizures and to trigger therapy to prevent clinical epileptic attacks (Litt & Echauz, 2002; McSharry, Smith, & Tarassenko, 2003). Treatments such as electrical stimulation or focal drug infusion could be given on demand and might eliminate side effects in some patients taking antiepileptic drugs.

On the other hand, if drug control of epileptic seizures is not successful and if the epileptic seizures are serious enough, then a further option for treatment is surgery. Epilepsy surgery outcome strongly depends on the epileptic seizure origin localization. The analysis of ictal EEG recordings (scalp or intracranial) is a gold standard for definition of localization of an epileptic seizure origin. Several linear (Parra, Spence, Gerson, & Sajda, 2005) and nonlinear methods (Acar, Aykut-Bingol, Bingol, Bro, & Yener, 2007) for analysis of epileptic EEG recordings as well as multi-way arrays models (Miwakeichi et al., 2004) have been used to understand the complex structure of epileptic seizure and localize seizure origin.

Table 1 shows a number of automated epileptic seizure detection methods found in the literature which is evaluated using the same dataset (Andrzejak et al., 2001). In Table 1, all methods are listed with their methodological standards (detection method, dataset, and classification accuracy). The dataset described in (Andrzejak, et al., 2001) is used for training and evaluation of these methods. This dataset includes five subsets five sets (denoted as *Z*, *O*, *N*, *F* and *S*), each containing 100 single-channel EEG segments of 23.6 sec duration, with sampling rate of 173.6 Hz. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. Sets *Z* and *O* consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open (*Z*) and eyes closed (*O*), respectively. Sets *N*, *F*, and *S* originated from an EEG archive of presurgical diagnosis. Segments in set *F* were recorded from the epileptogenic zone, and those in set *N* from the hippocampal formation of the opposite hemisphere of the brain. While sets *N* and *F* contained only activity measured during seizure-free intervals, set *S* only contained epileptic seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using a 12-bit resolution and they have the spectral bandwidth of the acquisition system, which varies from 0.5 to 85 Hz.

Epileptic Seizure Detection Method				
Author(s)	Year	Feature Extraction	Classification	Dataset Accuracy (%)
Nigam & Graupe Srinivasan et al	2004	Nonlinear pre-processing filter	Diagnostic neural network	Z-S 97.2
	2005	Time & Frequency domain analysis	Recurrent neural network	Z-S 99.6
Kannathal et al Kannathal et al	2005a	Chaotic measures	Surrogate data analysis	Z-S 90
	2005b	Entropy measures	Adaptive neuro-fuzzy inference system	Z-S 92.22
Güler & Übeyli	2005	Wavelet transform	Adaptive neuro-fuzzy inference system	Z-O-N-F-S 98.68
	2005	Lyapunov exponents	Recurrent neural network	Z-F-S 96.79
Übeyli	2006	Lyapunov exponents	Artificial neural networks	Z-F-S 95
Sadati et al	2006	Wavelet transform	Adaptive neuro-fuzzy network	Z-F-S 85.9
Adeli et al	2007	Wavelet transform & Chaos analysis	Statistical analysis (Analysis of variance-ANOVA)	Z-F-S -
Dastidar et al	2007	Wavelet transform & Chaos analysis	K-means clustering, Discriminant analysis, Artificial neural networks	Z-F-S 96.7
Güler & Übeyli	2007	Wavelet transform & Lyapunov exponents	Support vector machines	Z-O-N-F-S 99.28
Polat & Günes Subasi	2007	Fast Fourier transform	Decision Tree	Z-S 98.72
	2007	Wavelet transform	Mixture of expert model	Z-S 95
Tzallas et al	2007a	Time-frequency analysis	Artificial neural networks	Z-S 100
				Z-F-S 99.28
				ZONF-S 97.73
				ZO-NF-S 97.72
Tzallas et al	2007b	Time-frequency analysis	Artificial neural networks	Z-S 100
				Z-F-S 100
Übeyli & Güler Srinivasan et al	2007	Eigenvector methods	Mixture of expert model	Z-O-N-F-S 89
	2007	Approximate Entropy	Artificial neural networks	Z- O-N-F-S 98.60
Polat & Günes	2008a	Principal Component Analysis & Fast Fourier transform	Artificial immune recognition system	Z-S 100
				Z-S 100

Author(s)	Year	Epileptic Seizure Detection Method			Dataset	Accuracy (%)
		Feature Extraction	Classification			
<i>Polat & Güİnes</i>	2008b	Wavelet transform & Fast Fourier transform & Autoregressive model	Decision Tree		Z-S	99.32
<i>Chua et al</i>	2008	Higher order spectra & Power spectral density	Gaussian mixture model		Z-F-S	93.11
<i>Dastidar et al</i>	2008	Principal Component Analysis	Artificial neural networks		Z-F-S	99.3
<i>Ocak</i>	2008	Wavelet transform & Approximate entropy & Genetic algorithm	Learning vector quantization		ZNF-S	98
<i>Mousavi et al</i>	2008	Wavelet transform & Autoregressive model	Artificial neural networks		Z-N-S	96
<i>Übeyli</i>	2008a	Eigenvector methods	Support vector machines		Z-O-N-F-S	99.30
<i>Übeyli</i>	2008b	Wavelet transform	Mixture of expert model		Z-F-S	93.17
<i>Chandaka et al</i>	2009	Cross correlation	Support vector machines		Z-S	95.95
<i>Ocak</i>	2009	Wavelet transform & Approximate entropy	Surrogate data analysis		ZNF-S	96.65
<i>Guo et al</i>	2009	Wavelet transform & Relative wavelet energy	Artificial neural networks		Z-S	95.2
<i>Tzallas et al</i>	2009	Time-frequency analysis	Naives Bayes, k-nearest neighbor classifier, Logistic regression, Decision trees, Artificial neural networks		Z-S Z-F-S Z-O-N-F-S	100 100 89
<i>Übeyli</i>	2009a	Eigenvector methods	Recurrent neural network		Z-O-N-F-S	98.15
<i>Übeyli</i>	2009b	Wavelet transform	Probabilistic neural networks		Z-O-N-F-S	97.63
<i>Guo et al</i>	2010a	Wavelet transform & Approximate entropy	Artificial neural networks		Z-S ZONF-S	99.85 98.27
<i>Guo et al</i>	2010b	Wavelet transform & Line length feature	Artificial neural networks		Z-S ZONF-S ZO-NF-S	99.6 97.75 97.77
<i>Liang et al</i>	2010	Time frequency analysis & Approximate entropy	Linear least squares, Linear discriminant analysis, Support vector machines		ZONF-S Z-F-S Z-O-N-F-S	98.51 98.67 85.9

Table 1. Classification accuracies (in percent) obtained by automated epileptic seizure methods which are evaluated using a publicly available dataset (Andrzejak, et al., 2001).

Author(s)	Year	Epileptic Seizure Detection Method		Dataset
		Feature Extraction	Classification	
Subasi & Gursoy	2010	Wavelet transform & Principal component analysis & Independent component analysis & Linear discriminant analysis	Support vector machines	Z- S
Naghsh-Nilchi & Aghashahi	2010	Eigenvector methods & MUSIC	Artificial neural networks	Z- N- S
Altunay et al	2010	Linear prediction filter	Thresholding function	Z- O- N
Übeyli	2010a	Burg autoregressive & Moving average & Least squares modified Yule-Walker autoregressive moving average	Support vector machines	Z- S
Übeyli	2010b	Lyapunov exponents	Probabilistic neural networks	Z- O- N
Lima et al	2010	Wavelet transform	Support vector machines	Z- S
Guo et al	2011	Genetic programming based feature extraction system	K-nearest neighbor classifier	Z- S Z- F- S
Wang et al	2011	Wavelet transform & Shannon entropy	K-nearest neighbor classifier	Z- S
Isçan et al	2011	Cross correlation & Power spectral density	Support vector machines, Decision tree, Quadratic analysis, linear discriminant analysis, Naïve Bayes, K-nearest neighbor classifier	Z- S
Martinez-Vargas et al	2011	Time-frequency analysis	Thresholding function	ZO- NF
Orhan et al	2011	Wavelet transform	K-nearest neighbor classifier, Artificial Neural Network	Z- S Z- F- S ZO- NF ZO- NF ZONF-

Z: (Healthy) Relaxed in an awake state with eyes open, O: (Healthy) Relaxed in an awake state with eyes closed, N: Normal, F: Focal, S: Seizure, NF: Non-focal, ZONF: Z, O, N, F, S

3. Conclusion

Locating epileptic activity in the form of epileptic seizures or inter-ictal spikes in EEG recordings (usually lasting days or weeks in case of long-term recordings) is a demanding, time-consuming task because this activity constitutes a small percentage of the entire recording. This difficulty has motivated the development of automated methods that scan, identify, and then present to a neurophysiologist epochs containing epileptic events. Two types of automated methods for analysis of epileptic EEG recordings have been reported in the literature: those aimed at inter-ictal spike detection, and those aimed at epileptic seizure analysis and characterization of abnormal EEG activities in long-term recordings. In this chapter, a literature survey of the significant and recent studies that are concerned with effective detection of spike and epileptic seizures using EEG signals are presented. The main goal behind this review is to assist the researchers in the field of EEG signal analysis to understand the available methods and adopt the same for the detection of neurological disorders associated with EEG recordings.

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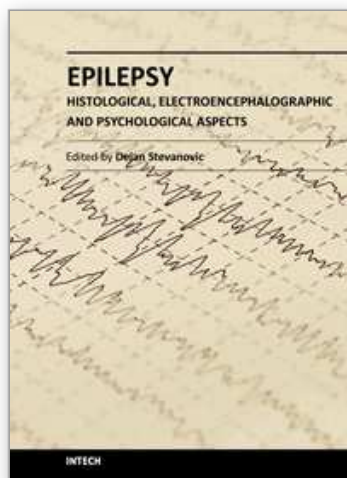
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中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

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