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Seizure Detection Algorithms Based on Analysis of EEG and ECG Signals: a Survey

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Epilepsy is a chronic disorder of the CNS that predisposes individuals to recurrent seizures. Computerized seizure detection algorithms will enable alerting systems that may decrease the harm of the seizures. This paper attempts to provide a comprehensive survey of different types of seizure detection algorithms and their potential role in diagnostic and therapeutic applications. Major recent algorithms use electroencephalogram (EEG) and electrocardiogram (ECG) signals to detect the seizure onset and seizure event. In these algorithms, various features are extracted from the EEG signal alone or in concert with the ECG signal until the patients are classified into two classes, seizure and non-seizure. We identify three major categories for seizure detectors; EEG-based seizure-event detectors, EEG-based seizure-onset detectors, and EEG/ECG-based seizure-onset detectors. In addition, some other related issues, such as dataset and evaluation measures, are also discussed. Finally, the performance of algorithms is evaluated, and their capabilities and limitations are described.

Keywords: epilepsy, seizure detection algorithm, EEG, ECG, feature extraction, classification.

INTRODUCTION

Epilepsy is a chronic disorder of the CNS that predisposes individuals to recurrent seizures. Electrographically, a seizure is a sudden transient aberration in the brain electrical activity that produces disruptive sensory and motor behavioral symptoms. These symptoms range between a lapse in attention, a sensory hallucination, or a whole-body convulsion [1]. Epilepsy is not a "single" disease but a family of syndromes that share features of the recurrent seizures. Epilepsy may develop as a result of inheriting mutations in molecular mechanisms that regulate neuronal behavior, migration, and/or organization. Alternatively, it may develop as a result of brain (craniocerebral) trauma, stroke, some cerebral infections, or brain malignancy [2]. Fifty million people worldwide have epilepsy. In the United States, epilepsy affects 3 million people and is the third most common neurologic disorder after Alzheimer's disease and stroke [3]. In an unfortunate subset of 1.2 million individuals, frequent and unpredictable seizures persist despite treatment by one or multiple anti-epileptic drugs. These types of seizures are known as medically intractable seizures [4]. The latter severely limit the independence and mobility of an individual and can result in social isolation and economic hardship. Most disturbing is that refractory seizures significantly increase an individual's chance of experiencing burns, lacerations, skull fractures, and even sudden unexpected death [5]. The negative influence of uncontrolled seizures extends beyond the individual to affect their family members, friends, and the whole of society. The families and friends of people with epilepsy experience chronic anxiety and adapt their lives to ensure the safety of their loved one [6]. Society incurs an annual loss of 12.5 billion dollars in health care costs and losses in productivity [7]. There is a need for novel therapies that better control seizures, as well as for technologies that help both the individual and their family to cope with the consequences of seizures.

Among novel therapeutic systems, local electrical stimulators, such as vagus nerve stimulators (VNS) [8] and trigeminal nerve stimulators (TNS) [9], are employed to stop the headway of a seizure prior to the extension of clinical symptoms. In these systems, the mass brain electrical activity (EEG) alone or in concert with other physiological signals (ECG) of a patient are recorded and monitored by portable [10] or wearable [11] devices in order to recognize the seizure. Computerized seizure detection algorithms

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will enable novel therapeutic and alerting systems that may decrease the harm of the seizures. A therapeutic system capable of detecting and reacting to the onset of a seizure may administer a local electrical [12], thermal [13], or neurochemical [14] stimulus that halts the progression of a seizure prior to the development of the symptoms. Moreover, just-in-time local therapy can relieve patients of the toxic side effects that accompany systemic administration of multiple anti-epileptic drugs. An alerting system (Fig. 1) equipped with seizure onset detection can warn the patient of the seizure prior to the development of debilitating symptoms or can notify a family member so that the consequences of a seizure are limited [15]. Knowledge that a reliable warning will be issued rapidly following seizure onset may restore within individuals the confidence to overcome the limits on life that accompany seizures.

A seizure detector can be classified either as a seizure-onset detector or as a seizure-event detector. The purpose of the seizure-onset detector is to recognize that a seizure has started with the shortest possible delay but not necessarily with the highest possible accuracy [16]. In contrast, the purpose of the seizure-event detector is to identify seizure with the greatest possible accuracy but not necessarily with the shortest delay [17]. Figure 2 shows categorization of the seizure detection algorithms. Seizure-onset detectors can facilitate the initiation of delay-sensitive diagnostic, therapeutic, and alerting procedures. Within the realm of diagnosis, seizure-onset detectors can be used to quickly initiate functional neuroimaging studies designed to localize the cerebral origin of a seizure [18]. Within the realm of therapy, seizure-onset detectors can be used to trigger neurostimulators designed to affect the progression of a seizure [19]. Within the realm of alerting, seizure-onset detectors can prompt a patient or a care provider to ensure safety or administer a fast-acting anticonvulsant. Seizure-event detectors can enable physicians to better titrate therapy (pharmacological or otherwise) over time [20]. A seizure-event detector within the ambulatory setting can provide physicians with a summary of the number, frequency, duration, and time of individual seizure experiences. By correlating this information with different medication regimens, a physician can more quickly decide on a treatment plan that maximally benefits the individual.

Research on seizure detection methods began with the development of seizure-event detectors [21]. The developed detectors were meant to detect seizures of any individual with epilepsy, i.e., they were patient-nonspecific. The variability within EEGs severely limited the detection accuracy of these patient-nonspecific detectors. To improve the performance, investigators developed patient-specific event detectors, i.e., detectors that could be "trained" to the EEG of an individual [22]. These detectors exhibited improved performance because seizure and non-seizure EEGs recorded from an individual exhibit less variability [23].

Seizure-onset and seizure-event detectors are often based on analysis of EEG signals. The EEG is a multichannel recording of the field electrical activity generated by enormous numbers of neurons within different brain regions [24]. The physics of EEG generation constrains both the origin and characteristics of neural activity visible within the scalp EEG. In particular, the neurons that contribute the most to the scalp EEG are those localized in closest vicinity to the scalp surface. In contrast, the activity of neurons buried within deep brain

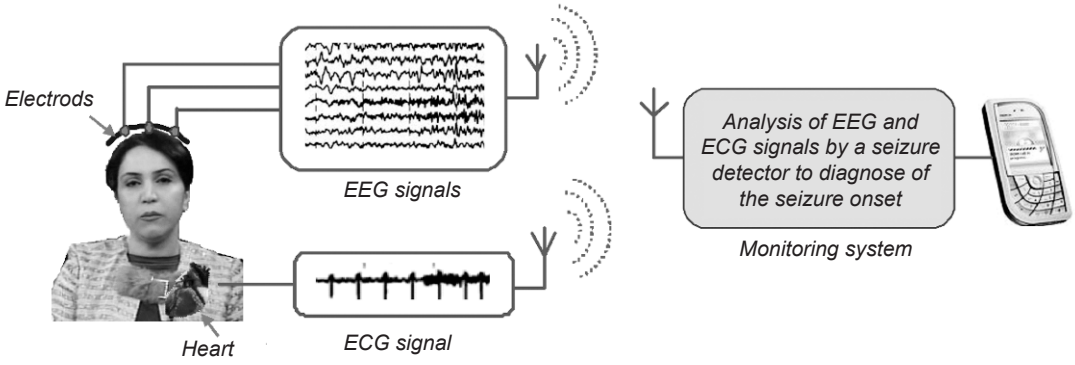

Fig. 1. Block diagram of an alerting system.

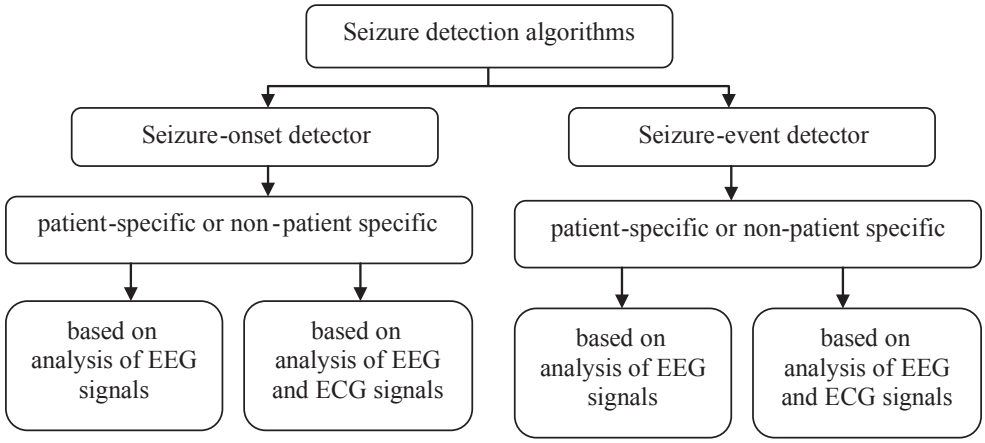

Fig. 2. Categorization of the seizure detection algorithms.

structures is almost not observable. Furthermore, the cerebrospinal fluid and skull surrounding the brain act as attenuators that greatly diminish the amplitude of high-frequency neural oscillations [25]. An important consequence of these physical limitations is that certain types of seizures, namely those involving a small deep region within the brain, practically cannot be observed using the scalp EEG. The EEG composition is usually classified as having a delta component with the dominant frequency $f < 4$ Hz, a theta component $4 < f < 8$ Hz, an alpha component $8 < f < 12$ Hz, a beta component $12 < f < 30$ Hz, and a gamma component $f > 30$ Hz [26].

Typically, following the onset of a seizure, the set of EEG channels, as well as the spectral content of the rhythmic activity, varies across individuals [27]. Furthermore, the EEG signature of one patient's seizure may closely resemble the signature of abnormal non-seizure EEG gathered from the same patient or from a different patient [28]. For example, two seizure events within the EEG of a patient are shown in Fig. 3A, B. Both seizures appear on the same channel and have the similar rhythmic characteristics. Figure 3C, D shows the seizure within EEG for another patient. The seizure event occurs on different channels and has dissimilar rhythmic activity in comparison with the first patient. So, the detector must be individually designed for each patient in order to achieve the best performance, i.e., the classifier must be trained based on the extracted features from seizure and non-seizure EEG signals for each patient. When the epileptic neural network is deep within the brain, the scalp EEG may reflect physical sequelae of the seizure, such as repetitive eye-blinks (eye flutter) or muscle contractions, before reflecting hypersynchronous neural activity. Seizures of this type are difficult to detect with a high specificity and short latency, since the activities, such as eye flutter and muscle contractions, are routinely observed as the individual partakes in the activities of daily life [29].

In order to detect these types of seizures, a detector requires information beyond that within the scalp EEG to ascertain whether a seizure is taking place or not. The additional information can be derived using some other physiological signal whose dynamics are influenced by the seizure. The second physiological signal and the scalp EEG will complement each other and improve seizure onset detection. The changes in each of these signals suggesting the onset of a seizure rarely coincide during non-seizure states and often coincide at the time of an actual seizure. The patient-related specificity remains essential to the success of this approach since the manner with which the scalp EEG and the secondary signal change during seizures and non-seizures varies across patients. For example, seizures resulting in repetitive motor activity may become readily detectable if scalp EEG data are supplemented with accelerometer sensor data [30]. For other types of seizures, especially those originating within or spreading to the temporal lobes, seizures are associated with electrocardiographic (ECG) changes [31]. The most common ECG change associated with seizures is a heart rate (HR) acceleration (tachycardia) [32]. Figure 3E shows an example of an electrographic seizure, which begins at the 56th sec. It involves a 12-sec-long period of low-amplitude EEG activity across most EEG channels and, at the same time, the patient's HR increases.

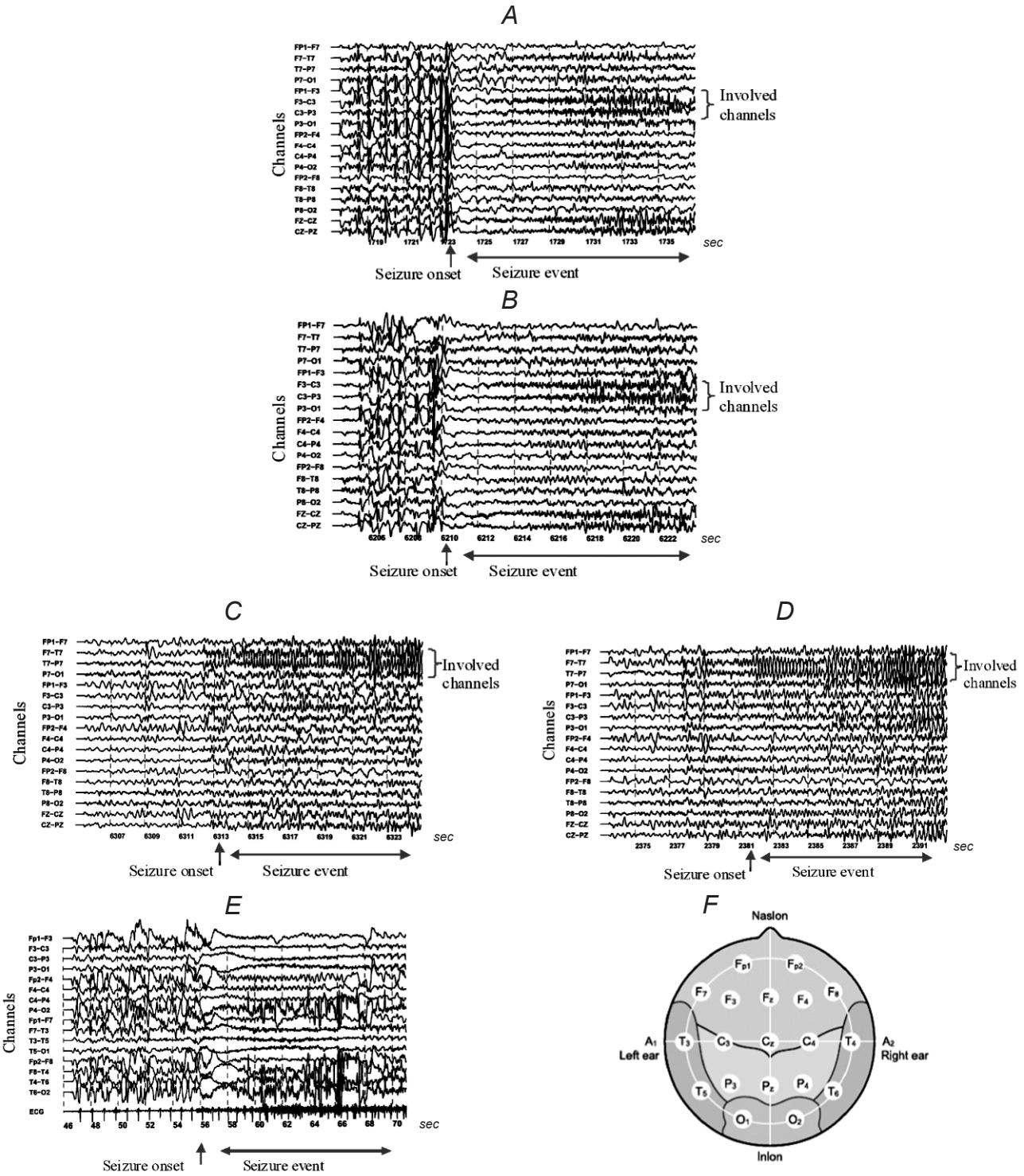

Fig. 3. Seizure events within the EEG of different patients. A) The seizure starts at sec 1723 and involves the F3-C3 and C3-P3 channels. B) The seizure starts at sec 6210 and involves the F3-C3 and C3-P3 channels. C) The seizure starts at sec 6313 and involves the F7-T7 and T7-P7 channels. D) The seizure starts at sec 2381 and involves the F7-T7 and T7-P7 channels. E) The seizure starts at sec 56 and has a low-amplitude EEG activity across most EEG channels for 12 sec; at the same time, the patient's heart rate accelerates at sec 56. F) The channels arrayed symmetrically across the scalp EEG.

STRUCTURE OF SEIZURE DETECTION ALGORITHMS

In this section, we present the general architecture of seizure detection algorithms based on the analysis of EEG alone or in concert with ECG signals. The general structure of these algorithms is shown in Fig. 4; it includes two basic steps, feature extraction and feature classification.

Classification is the process of assigning an observation to one of predefined classes or categories in a manner that minimizes the error of classification. In the seizure detection problem, the observation is an EEG epoch, and the two classes are seizure activity (class one) and non-seizure activity (class two). Determining the class label of an observation involves two steps. First, salient features that are most discriminative between instances of each class are extracted from the observation and assembled into a vector of the features. The success of a classification task depends strongly on which features are extracted from an observation and the classifier used to determine the class label. Features that provide the most diversity between observations of two classes and the most resemblance between observations of one class improve the detection performance. Table 1 shows some effective features that can be extracted from the frequency and time domains of EEG and ECG signals. These features include a large number of the single-channel EEG features, such as power estimations in several frequency ranges, as well as several measures of the HR variability described in time and frequency domains of the *R-R* time series extracted from the ECG features. The *R-R* interval is defined as the time (sec) between the adjacent *R*-wave maximum points. The relative scale energy is defined as the ratio of the energy in the coefficients of a given scale to the energy of the coefficients in all scales. The relative energy of a given wavelet scale is essentially the proportion of signal energy contained in that scale. This feature is directly calculated from the wavelet coefficients and not from the amplitudes of the segment decomposition. It serves as a measure of arhythmicity, as a sustained elevated value in one scale indicates a relatively constant frequency in the signal. The coefficient of amplitude variation is defined as the square of the ratio of the standard deviation to the mean of the peak-to-peak amplitudes. The waveform decomposition method is used to calculate it as well. This feature serves as a measure of variability of the signal amplitude. A low value indicates little variation.

There are different algorithms to diagnose the seizure with the above structures, and these can be categorized into three groups, EEG-based seizure-event detection algorithms, EEG-based seizure-onset detection algorithms, and EEG-ECG-based seizure-onset detection algorithms.

EEG-Based Seizure-Event Detectors. One of the earliest patient-nonspecific seizure-event detectors was the one developed by Gotman et al. [33] in 1982. This algorithm searches EEG channels for the presence of rhythmic activity with a dominant frequency between 3 and 20 Hz. It uses the frequency spectrum analysis to detect periodic discharges. The EEG is divided into 10-sec-long windows moving in 2.5-sec increments. The frequency spectrum of each 10-sec-long epoch is calculated, and a number of features, such as the frequency and width of the dominant spectral peak, as well as the relative power of the frequency band, are extracted to detect seizures. The Gotman algorithm successfully detects seizures whose evolution includes sustained rhythmic activity with a fundamental frequency below 20 Hz. It is not successful in detecting seizures where EEG contains a mixture of frequencies or those with low-amplitude high-frequency activity.

Since the scalp EEGs of individuals with epilepsy contain pathological, normal, and artifact-induced

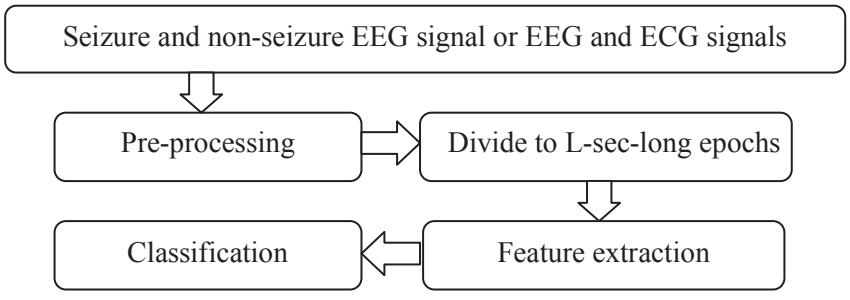

Fig. 4. General structure of the seizure detection algorithms.

TABLE 1. Effective Features Extracted from the Frequency and Time Domains of EEG and ECG Signals

Frequency/time domains	Description
EEG signals	
Frequency domain	Mean-squared error of estimated AR models (model order 10) [12], [26], [41], [56] Relative power of spectral band delta (0.1-4 Hz) [42], [29], [34], [53] Relative power of spectral band theta (4-8 Hz) [42], [29], [37], [53] Relative power of spectral band alpha (8-15 Hz) [42], [13], [30], [53] Relative power of spectral band beta (15-30 Hz) [42], [53], [30], [54] Relative power of spectral band gamma (30-200 Hz) [55], [19], [30], [54] Spectral edge frequency [25], [56], [16], [34], [46] Spectral edge power [11], [17], [53], [57] Decorrelation time [27]
Time domain	First statistical moment of EEG amplitudes (mean) [10], [23], [41], [58] Second statistical moment of EEG amplitudes (variance) [10], [23], [41], [58] Third statistical moment of EEG amplitudes (skewness) [10], [23], [41], [58] Fourth statistical moment of EEG amplitudes (kurtosis) [10], [23], [41], [58] Long-term energy [15] [24], [44], [59]
Time and frequency domain	Energy of the wavelet coefficients [11], [25], [43], [60], [37], [26], [42], [56], [63]
ECG features	
Frequency domain	Very low frequency (VLF): <0.04 Hz [33], [39], [20] Low frequency (LF): 0.04-0.15 Hz [33], [39], [20]
Time domain	Mean *R-R* intervals (msec) [61], [20], [28] Variance of *R-R* intervals (msec) [33], [46], [28] Maximum *R-R* interval (msec) [33], [46], [28] Minimum *R-R* interval (msec) [33], [46], [28] Mean heart rate (min^{-1}) [33], [46], [20] Variance of the heart rate (min^{-1}) [62] Maximum heart rate (min^{-1}) [62], [64] Minimum heart rate (min^{-1}) [62] Approximate entropy (ApEn) describing the complexity and irregularity of the *RR* intervals

bursts of rhythmic activity, a significant fraction of detections produced by the Gotman algorithm are not associated with seizures [34]. So, investigators have developed seizure-event detectors that utilize more sophisticated signal processing to characterize the rhythmicity associated with seizures. Liu's algorithm [35] also relies on the periodicity as the dominant characteristic of seizures in the EEG signals. The degree of periodicity in the autocorrelation function of 30-sec-long epochs of EEG data is scored and used to classify the epoch as seizure or non-seizure. Wilson's algorithm [36] decomposes 2-sec-long EEG epochs from each input channel into time-frequency "atoms" using the matching pursuit algorithm. Wilson then employs hand-coded and neural network rules to determine whether features derived from the "atoms" of a channel are consistent with a seizure taking place on that channel. The thresholds for some of the neural network rules are determined using both archetypal seizures from individuals with epilepsy and background EEG from individuals without epilepsy.

Hassanpour et al. [37] investigated a time-frequency domain (TFD)-based seizure-event detection algorithm. The EEG signal was segmented into 30-sec-long epochs. A singular value decomposition (SVD) was performed on the TFD representation of each epoch. To discriminate between seizure and non-seizure activities in each EEG epoch using the TFD, this method uses two left and two right singular values (SVs). The left and right SVs correspond to the time- and frequency-domain components of the signal. The extracted features through the histograms of the four SVs are

organized into a feature vector and fed into a trained neural network to classify each feature vector as seizure or non-seizure.

EEG-Based Seizure-Onset Detectors. Saab et al. [38] designed an automatic seizure onset detection that was used on-line within a long-term monitoring facility. It employs a Bayesian formulation to output a variable based on the probability that an EEG section contains seizure activity. Saab's algorithm uses features derived from a wavelet decomposition of each EEG channel to estimate the probability of a seizure. Whenever the probability exceeds a user-defined threshold for a given period of time, the algorithm declares the onset of a seizure. Qu et al. developed the first patient-specific seizure-onset detection algorithm [39]. Qu's algorithm relies on a nearest-neighbor classifier to assign a list of features to the seizure or non-seizure classes. The classifier is trained on seizure and non-seizure feature vectors derived from the available EEG channels and declares a seizure if the set of positively classified channels matches half of those chosen by an expert.

Meier et al. [40] grouped seizures in a database into six categories based on the frequency of the dominant rhythm that appears following the seizure onset. He then trained a set of support-vector machines, one for each seizure type, to determine whether an extracted feature vector from an EEG epoch is consistent with one of the seizure types. Instead of extracting and then classifying feature vectors from one channel to another, Meier extracted a single feature vector that includes the average (across-channels) of signal properties, such as the number of zero crossings, wavelet coefficient power, and cross-correlation.

Celka's algorithm [41] is a time-domain method employing patient-specific pre-processing. The pre-processing involves estimating an autoregressive moving average model of the pre-recorded normal EEG. The corresponding inverse is applied to the signal being analyzed, leaving only seizure components and Gaussian white noise. A SVD-based algorithm is then used to extract seizure features from noise.

Shoeb presented a patient-specific seizure-onset detection algorithm [42]. It extracts eight features from a 0-25 Hz frequency band by means of a 3 Hz bandwidth filter, and a support vector machine (SVM) classifier is used to classify the feature vectors. The detector passes L-sec-long epochs from each N EEG channels through a filter bank. In turn, the filter bank computes M features for each channel, which correspond to the energies within M frequency bands. The M extracted features from each of the N channels are then concatenated to form an $M \times N$ element vector that automatically captures the spectral and spatial relations between channels. Finally, the feature vector is assigned to the

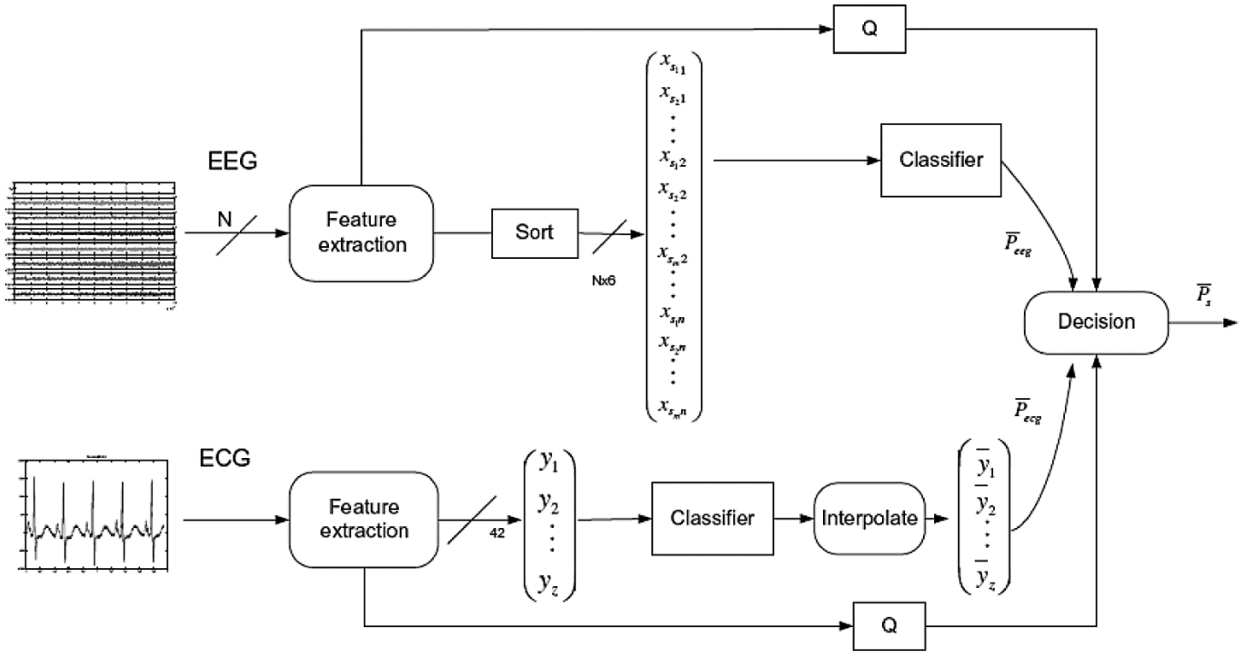

Fig. 5. Structure of Barry's algorithm [46].

seizure or non-seizure class using a two-class SVM classifier. Since seizure and non-seizure activities are generally stereotypical for a patient and highly variable across patients, the SVM is trained on discriminating seizure and non-seizure vectors from a single patient. The training non-seizure vectors are extracted from *H* hours of the continuously recorded scalp EEG. The seizure vectors are derived from the first *S* sec following the onset of *K* training seizures.

EEG and ECG-Based Seizure-Onset Detectors. Several authors have published data on the relationship of changes in the ECG signal with adult epileptic onset and its utility for epileptic seizure detection. As was mentioned, seizures involve the hyperactivity and hypersynchrony of a population of neurons. At the level of the scalp EEG, this coherent neural firing gives rise to rhythmic activity with a dominant frequency between 0 and 25 Hz. However, when the underlying neural hypersynchrony involves a neural network deep within the brain, the earliest scalp EEG changes may not reflect the above neuronal hypersynchrony. In order to detect seizures, additional information can be obtained from a second physiological signal, such as the ECG signal. The most common ECG change associated with seizures is an HR increase.

To design a seizure-onset detector based on the analysis of EEG and ECG signals, the features are extracted from the seizure and non-seizure EEG signals of the patient and simultaneously combined with the extracted features from the ECG signals. The spectral and spatial features can be obtained from the energy spectrum of each EEG channel. Also, the HR mean and the instantaneous HR can be extracted from ECG signals. For example, Quint et al. [43] studied changes in the ECG during epileptic seizure onset in adults and concluded that characteristic changes in the mean heart period are frequently, if not always, present upon detection of seizure onset in adult EEG. Zijlmans et al. [44] attempted to rigorously document cardiac behavior during epileptic seizure onset in adults. These authors found that there was an increase in the HR of at least 10 min^{-1} in 73% of seizures (93% of patients) around the point of seizure onset from a point 30 sec prior to the moment of clinical or electrographic seizure onset. Kerem et al. [45] used the *R*-*R* interval time series to forecast epileptic seizure in adults using successive HR timing intervals in an unsupervised fuzzy clustering algorithm. Barry et al. [46] presented a seizure onset detection algorithm based on EEG and ECG signals. It extracted six features (dominant spectral peak, power ratio, bandwidth of the dominant spectral peak, nonlinear energy, spectral entropy, and line length) from EEG signals and six features (mean *R*-*R* interval, standard deviation of these intervals, mean *R*-*R* interval spectral entropy, mean change in the *R*-*R* interval, interval coefficient of variation, and interval power spectral density) from ECG signals. The *R*-*R* interval is defined as the time (sec) between adjacent *R*-wave maximum points described by Benitez [47]. Figure 5 shows the general structure of the Barry's algorithm.

Nasehi et al. developed a seizure onset detection algorithm based on the analysis of EEG and ECG signals to detect seizure onsets that are not associated with rhythmic EEG activity [48]. In this algorithm, *L*-sec-long epochs from seizure and non-seizure EEG signals are decomposed by Gabor functions and represented in the spatial, spectral, and temporal domains. Then, five features, such as number of zero coefficients, smallest and largest coefficients, and mean and standard deviation of the coefficients, are extracted from each sub-representation. Synchronously, four features, such as the mean HR, instantaneous HR, power ratio, and spectral entropy, are extracted from *L*-sec-long ECG epochs. Finally, a probabilistic neural network classifier is employed to train on the extracted features from seizure and non-seizure EEG-ECG signals of each patient for determination of optimal nonlinear decision boundaries.

EEG AND ECG DATASET AND EVALUATION MEASURES.

The seizure detection algorithms require a training dataset of EEG or ECG signals. Since these databases were constructed to empirically evaluate recognition algorithms in certain domains, we first review the characteristics of these databases and their applicability to seizure detection. Then, the evaluation measures are introduced.

Dataset

SMC Dataset. This dataset is collected from the Epilepsy Telemetry Unit at the Montreal Neurological Institute and Hospital, using the Stellate Harmonic system for EEG monitoring (Stellate, Montreal, Canada). Data are sampled at 200 sec^{-1} after filtering between 0.5 and 70 Hz,

and bipolar electrode montages of either 24 or 32 channels are used in the analysis. This dataset consists of EEG recording from 28 patients that contained 652 h of EEGs recorded and 126 seizures. Further information about this data is available in [49].

CHB Dataset. This dataset consists of continuous scalp EEG recording from 23 pediatric patients undergoing medication withdrawal for epilepsy surgery evaluation at the Children's Hospital (Boston, USA). The EEG was sampled at 256 sec^{-1} and recorded using an 18-channel 10-20 bipolar montage. Overall, this 23-patient dataset contained 844 h of continuously recorded EEGs and 163 seizures. The scalp EEG dataset is segmented into records. Typically, a record is 1 h long. Records that do not contain a seizure are called non-seizure records, and those that contain one or more seizures are called seizure records. Further information about this data is available in [50].

KCH Dataset. A dataset of 12 records from 10 term neonates containing 633 labeled seizure events with a mean seizure duration of 4.60 min were recorded and analyzed. The records had a mean duration of 12.84 h. Each record contained 7 to 12 channels of EEG and one channel of simultaneously acquired ECG. Ten records sampled at 256 sec^{-1} were made in the neonatal intensive care units of the Unified Maternity Hospitals in Cork (Ireland) using the Viasys NicOne video-EEG system. The remaining recording, sampled at 200 sec^{-1}, was recorded at Kings College Hospital, London (Great Britain) on a Tele factor Beehive video-EEG system. A total of 154.1 h of EEGs and ECGs were analyzed. Further information abut this data is available in [51].

Freiburg Dataset. This dataset consists of continuous scalp EEG recording from 57 pediatric patients undergoing medication withdrawal for epilepsy surgery evaluation at University Hospital Freiburg (Germany). The EEG was sampled at 256 sec^{-1} and recorded using a 6-channel 10-20 bipolar montage. Overall, this 57-patient dataset contained 1400 h of continuously recorded EEGs and 91 seizures. Further information about this data is available in [52].

Evaluation Measures

Five metrics are usually used to characterize the performance of the seizure-detection algorithm.

Latency. The electrographic onset of a seizure refers to the onset of scalp EEG changes associated with a seizure. The clinical onset of a seizure refers to the onset of its physical or cognitive symptoms. In scalp EEGs, the electrographic onset of a seizure may or may not precede its clinical onset. The latency refers to a delay between the electrographic onset and detector recognition of seizure activity.

Sensitivity. The sensitivity refers to the proportion (percentage) of test seizures identified by a detector. A high sensitivity increases the capability of a detector to recognize seizures in order to initiate timely therapy procedures.

Specificity. The specificity refers to the number of times, over the course of an hour, that a detector declares the onset of seizure activity in the absence of an actual seizure.

FDR. The false detection rate is defined as the percentage of non-seizure epochs incorrectly identified as seizure epochs.

GDR. The seizure sensitivity, or good detection rate (GDR), is defined as the percentage of electrographic seizure events as defined by an expert in EEG-ECGs correctly identified by the detector.

PERFORMANCE EVALUATION OF ALGORITHMS AND DISCUSSION

Table 2 illustrates the comparison between the best seizure-detection algorithms that have been proposed in the literature. Gotman et al. [33] reported a GDR (or sensitivity) of 71% with 1.7 false detections per hour. The results of the Gotman method were validated in a subsequent paper [34] by analyzing a separate dataset containing 281 h of EEG data from 54 patients (again in three medical centers). The sensitivity of this set was 69% with a specificity of 2.3 per hour. Gotman's algorithm was not successful in detecting seizures with EEG containing a mixture of frequencies or those with low-amplitude high-frequency activity. Liu et al. [36] reported a sensitivity of 84% and a FDR of 98% for their proposed method. Wilson et al. [36] reported that their proposed algorithm detected 76% of 672 seizures gathered from 426 individuals with a sensitivity of 0.11 false detections per hour. It demonstrated poor specificity when the scalp EEG signal of patients was abnormal (non-seizure rhythmic activity). Hassanpour's algorithm [37] was evaluated on 8 patients. It showed an average sensitivity of 92.5% and a FDR of 3.7%.

Saab's algorithm [37] was evaluated on SMC

TABLE 2. Comparison of Performance of the Best Seizure Detection Algorithms

Algorithms	Sensitivity (%)	Specificity (false per h)	FDR (%)	GDR (%)	Latency (sec)	Dataset description
Gotman [34]	69	2.3	–	–	–	281 h from 54 patients
Liu [35]	84	–	–	98	–	281 h from 54 patients
Wilson [36]	76	0.11	–	–	–	672 seizures from 426 patients
Hassanpour [37]	92	–	3.7	–	–	64 seizures from 8 patients
Saab [38]	78	0.86	–	–	9.8	SMC dataset
Qu [39]	100	0.03	–	–	9.35	29 h and 47 seizures from 12 patients
Meier [40]	96	0.45	–	–	1.6	Freiburg dataset
Celka [41]	93	–	4	–	–	53 seizures from 4 patients
Shoeb [42]	96	0.07	–	–	4.6	CHB dataset
Kerem [45]	86	–	–	–	–	95 seizures from 8 patients
Barry [46]	74	–	13.18	97.52	–	KCH dataset
Nasehi [48]	79	–	12.47	98.25	4.7	KCH dataset

Footnote. FDR and GDR are, respectively, false and good detection rates.

dataset. This algorithm detected 78% of seizures with a median detection latency of 9.8 sec and a specificity of 0.86 false detections per hour. Saab reported that missed seizures included those with onsets characterized by focal activity, mixed frequencies, or short duration, and those false detections were mainly caused by short bursts of rhythmic activity, rapid eye blinking, and chewing. Qu's algorithm [38] was evaluated on 29.7 h and 47 seizures from 12 patients. This method detected 100% of seizures with an average delay of 9.35 sec and a specificity of 0.03 false detections per hour. The non-seizure EEG signals that Qu used to calculate the FDR of his algorithm were formed by concatenating segments of EEG extracted at regular intervals from several days of the dataset. When compared to Saab's work, Qu's work illustrates that a patient-specific approach can result in improved sensitivity and specificity, but not necessarily in an improvement in the detection latency. Meier's algorithm [39] is evaluated on the Freiburg dataset. It detected 96% of the test seizures with an average detection delay of 1.6 sec and specificity of 0.45 false detections per hour. Meier's approach depends on the test seizure being a member of one of the six defined categories, as well as it being recorded using the same number and position of channels used to record the training seizures. Seizures whose onsets lack the development of rhythmic activity and instead reflect physical sequelae of the seizure (such as eye flutter) do not fall within the defined categories. Consequently, such seizures will be detected later or not at all. Celka's algorithm [40] obtained a sensitivity of 93% and a false detection rate (FDR) of 4% for four neonatal subjects. In the reported results by Celka, channels known to contain seizures were chosen for processing. Although this does not bias the results on a per-channel basis, a real-time seizure detection system would require processing and polling of all channels in parallel, as the spatial location of the seizure is *a priori* unknown. Shoeb's algorithm [41] is trained on the CHB dataset. The algorithm detected 96% of 163 test seizures with a median detection delay of 4.6 sec and specificity of 0.07 false per hour. The latency, however, was large for some patients, which can arise from great similarity of seizure and non-seizure signals.

Zijlmans et al. [43] found that there was an increase in the HR of at least 10 min^{-1} in 73% of seizures (93% of patients) around the point of seizure onset from a point 30 sec prior to the moment of clinical or electrographic seizure onset. These results were estimated for 281 seizures in 81 epileptic patients.

The large size of this dataset provides high weight and statistical significance to the results presented. Kerem et al. [44] reported a prediction sensitivity of 86% for eight epileptic patients. Barry's algorithm [45] was evaluated on the KCH dataset. It could recognize 617 of 633 expert-labeled seizures with an FDR of 13.18%. Nasehi's algorithm [47] was evaluated on the KCH dataset. It could reach a mean GDR of 98.25% with an FDR of 12.47%. It also obtained a classification sensitivity of 79.66% and a mean latency of 4.7 sec.

CONCLUSION

This paper proposes an overview of the seizure detection algorithms based on the analysis of EEG and ECG signals. The basic structure of these algorithms is constructed in two main components, feature extraction and feature classification. The extracted features from EEG signals can be defined based on the power spectrum or representation forms of the signal that are provided by using wavelet transforms or Gabor filter banks of L-sec-long epochs of the EEG signals. Also, the HR acceleration can be considered as a feature extracted through ECG signals. All of these features and classifiers, such as SVM, artificial neural networks, and statistical classifiers, detect the seizure and non-seizure EEG signals. Five standard measures (latency, sensitivity, specificity, FDR, and GDR) are used to evaluate and compare the seizure detection algorithms. For the seizure-onset detection algorithms, the ability of the proposed algorithm to obtain smaller values of the latency is very important. For the seizure-event detection algorithms, the sensitivity measure is an important parameter in the evaluation of the ability of the presented algorithm.

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