Epileptic Seizures Classification Based on Long-Term EEG Signal Wavelet Analysis

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Abstract

Epilepsy is a complex neurological disorder recognized by abnormal synchronization of cerebral neurons, named seizures. During the last decades, significant progress has been done in automated detection and prediction of seizures, aiming to develop personalized closed-loop intervention systems. In this paper, a methodology for automated seizure detection based on Discrete Wavelet Transform (DWT) is presented. Twenty-one intracranial ictal recordings acquired from the database of University Hospital of Freiburg are firstly segmented in 2 s epochs. Then, a five-level decomposition is applied in each segment and five features are extracted from the wavelet coefficients. The extracted feature vector is used to train a Support Vector Machines (SVM) classifier. Average sensitivity and specificity reached above 93% and 99% respectively.

Keywords

Electroencephalogram (EEG) • Seizure • Epilepsy • Discrete wavelet transform (DWT)

Introduction

One of the most challenging brain disorders that has gained increasing attention the last decades is epilepsy. Epilepsy is characterized by recurrent seizures, which are brief episodes of involuntary movement caused by excessive electrical discharges in a group of brain cells. According to the latest World Health Organization (WHO) reports, epilepsy affects almost 1% of the world's population and is estimated that about 2.4 million people are diagnosed with epilepsy each year [1]. Furthermore, about 30% of children and adults suffering from seizure episodes are left untreated and without anti-epileptic drugs (AED).

The diagnosis and monitoring of seizures is done through neuroimaging and electrophysiological techniques. The electroencephalogram (EEG) is the diagnostic tool that continuously records the brain's electrical activity using electrodes as sensors to detect fluctuations of the emitted electric charges [2]. Based on the location of electrodes, EEG is discriminated in scalp EEG (sEEG), in which the electrodes are placed in the surface, and intracranial EEG (iEEG), in which the electrodes are placed invasively inside the brain.

Computerized methods and automated seizure detection systems have been developed utilizing different EEG databases, owing to the complexity of the disorder coupled with the multiple drawbacks of the visual inspection by neurophysiologists. A variety of methods has been validated with the database of epilepsy center of the University of Bonn, which is consisted of short-term (23.6 s) scalp and intracranial EEG recordings. However, a long-term dataset

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such as the one of Epilepsy Center of the University Hospital of Freiburg is closer to clinical recordings and provides more information for further developing seizure prediction algorithms.

Freiburg database has been extensively used by research groups worldwide. Different methodologies have been proposed including Wavelet Transform, Empirical Mode Decomposition (EMD) [3, 4] Principal Component Analysis (PCA) [5], Independent Component Analysis (ICA) [6], Fractal analysis [7, 8] or Fuzzy systems [9, 10]. The majority of them concur with a two-stage procedure, following a pattern recognition approach: feature extraction and classification.

Particularly, the Discrete Wavelet Transform (DWT) has been adopted by many researchers to decompose the recordings in certain sub-bands [11–15]. Then, significant features such as the coastline and Hjorth variance [11], the relative energy, the relative amplitude, the fluctuation index, the coefficient of variation [12], the wavelet variances [14], the lacunarity and the fluctuation index [13] or the diffusion distances [15] were extracted from the resulting signals. The extracted set of features was used as input to train either a Support Vector Machines (SVM) [12] or a Bayesian linear discriminant classifier (BLDA) [13, 15]. Finally, in study [14] Xie and Krishnan evaluated the performance of various classifiers (k-Nearest Neighbor, Fisher's linear discriminant, SVM) whereas in [11] a rule based approach was preferred instead of a classifier.

In this paper, an automated seizure detection methodology is presented based on DWT in order to divide EEG recordings to specific subbands and extract several features. Subsequently, these features are given as an input feature vector to train a SVM classifier. The methodology has been evaluated on 21 long-term intracranial EEG recordings for a binary classification problem and results are presented.

Materials and Method

The proposed work consists of four stages: segmentation, wavelet analysis, feature extraction and classification. In the first stage, a long-term EEG recording from ictal activity of each patient is segmented into 2 s windows. After that, a 5-level wavelet-decomposition is applied in each EEG segment dividing every signal into several frequency subbands. In the next stage, 5 features are calculated from each subband creating a feature vector. Finally, the feature vector is used to train a SVM classifier. In Fig. 1, a concise diagram of the proposed methodology is presented.

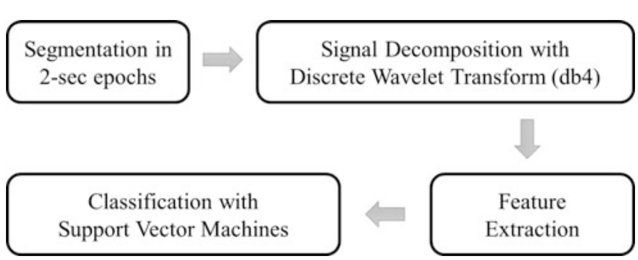

Fig. 1 A brief diagram of the proposed methodology

The Database

The methodology has been trained and tested on invasive EEG recordings from 21 patients suffering from medically intractable focal epilepsy. The dataset comes from the Epilepsy Center of the University Hospital of Freiburg and is now available through the EPILEPSIAE project [16]. The available data included six intracranial EEG channels (three focal and three extra-focal electrodes).

The EEG recordings obtained from 21 patients are separated into files of ictal (the period with seizure onset), preictal (the period before seizure onset) and interictal (the period between seizures) activity. Two–five seizure episodes were recorded for each patient lasting from several seconds to a few minutes. A total of 87 seizures, 509 h of interictal and 199 h of both pre-ictal and ictal EEG data are included in this large dataset.

In this methodology, only the first channel of an ictal recording of each patient is used, since the ictal recordings would contain more epileptic components and would provide better discrimination of "seizure" and "non-seizure" activity.

Preprocessing

The long-term EEG channel of each patient was initially divided into 2 s (512 samples), non-overlapping epochs leading to 1800 segments per patient. This window size proved to be the optimal after testing potential window sizes. Since the seizure duration ranges among [4.21–1071.5] s, the 2 s window was chosen aiming to accurately capture the subtle changes of EEG. Afterwards, the Discrete Wavelet Transform was applied in each one of the resulting segments.

Discrete Wavelet Transform

Wavelet Transform (WT) has gained significant ground in automated seizure detection scheme and is widely applied in numerous seizure detection studies.

Table 1 Frequency ranges with the corresponding wavelet decomposition levels

Frequency range (Hz)	Decomposed signal
64–128	D1
32–64	D2
16–32	D3
8–16	D4
4–8	D5
0–4	A5

According to Wavelet Analysis [17], a signal can be represented by a linear combination of a particular set of functions, obtained by dilating and translating a single function. This function is called mother wavelet and is used to decompose the initial signal into sub-signals of half its size and spectrum.

In Discrete Wavelet Transform (DWT) the scaling and translating parameters are represented in powers of two. The implementation of the DWT uses a series of quadrature mirror filters (QMF) described as high-pass and low-pass filters. In the first level of DWT, the input signal is simultaneously passed through the conjugate low and high pass filters. The obtained outputs are a set of coefficients called wavelet coefficients. The output of the low-pass filter, namely approximation, is sub-decomposed, whereas the output of the high-pass filter, namely detail, is not. The same procedure is recursively repeated, forming a single-side, pyramid-like architecture.

Choosing the number of decomposition levels and the appropriate mother wavelet is of primary importance. The number of decomposition levels is chosen based on the dominant frequency. The best mother wavelet function was selected, mainly among the Daubechies wavelets, after visual examination. In this study, a 5-level-decomposition transform is used and the family of Daubechies wavelets of order 4 (db4) is selected to decompose the signal. Table 1 shows the corresponding frequencies to the resulting decomposition levels.

Feature Extraction

In order to minimize the complexity and the computational time of the proposed methodology, the most representative and significant characteristics were extracted. Thus, in the present study five features were calculated in each decomposition level, namely energy, entropy, standard deviation, variance and mean of the absolute values of the wavelet coefficients. The final low-dimensional feature vector was used as an input to train an SVM classifier.

Classification

Support Vector Machines (SVM) is a machine learning technique for binary classifications problems. According to Machine Learning [18], non-linear instances that need to be classified are mapped to a high-dimension feature space. In this feature space instances are separated by a very clear gap, named hyperplane. The vectors that lie on the margin are called support vectors and they constitute the critical elements of the training set for the classification problem. The basic idea underlying this technique is to locate an Optimal Separating Hyperplane, which maximizes the distance between the margin and the support vectors and minimizes the classification error, in a projection space by solving a quadratic optimization problem. The kernel function that may be a linear, radial basis function (RBF), polynomial, or sigmoid kernels is responsible for the transformation to the higher dimensional space. In this study, RBF kernel function was used. Furthermore, two parameters were optimized in order to optimize the algorithm and therefore the classification results. A grid search was performed on the parameters C and γ, which are related with margin boundaries and the RBF kernel function respectively, using cross-validation.

Results

The Freiburg database is one of the most comprehensive, long-term datasets and a variety of classification problems are addressed based on its recordings. In an attempt to identify seizure episodes, one ictal recording from each one of the 21 patients was used. Since the onset and the offset of seizure episodes are known, the epochs between the seizure onset and offset were marked as "seizure" and the rest of the epochs as "non-seizure", forming the corresponding classes. Also, the 2 s duration epochs adjacent to the onset and offset were excluded from the subsequent processing and no annotation was added.

To validate the experiments, the 10-fold cross-validation technique was employed. In some patients, the non-seizure instances were tremendously more than the seizure ones, leading to unbalanced data and poor training of the classifier. Consequently, the data were rounded up by manually repeating seizure instances, until the seizure instances were approximately 10% of the non-seizure. Sensitivity, specificity and overall accuracy were calculated from the number of correctly/incorrectly classified instances, for evaluation of the classification performance. The obtained statistical results for each patient are described in Table 2. The best sensitivity (100%) was achieved for half of the patients (patients 1, 7, 9, 12, 13, 17, 18, 19, 20 and 21), while the lowest sensitivity was 45.30% obtained from the

Table 2 Sensitivity, specificity and accuracy results for each patient

Patient	Sensitivity	Specificity	Accuracy
1	100	100	100
2	95.24	99.83	99.37
3	97.80	99.83	99.64
4	98.90	100	99.90
5	99.44	100	99.95
6	98.58	99.77	99.64
7	100	99.94	99.95
8	96.72	100	99.69
9	100	100	100
10	95.03	99.65	99.21
11	45.30	99.20	93.78
12	100	99.94	99.95
13	100	100	100
14	87.85	99.65	98.53
15	60.99	99.45	95.61
16	93.37	100	99.37
17	100	99.94	99.95
18	100	100	100
19	100	100	100
20	100	100	100
21	100	99.89	99.90
Total	93.77	99.86	99.26

classification of the patient 11. Specificity was also high, reaching above 99% for all patients and ten patients among them reached 100%.

Discussion and Conclusions

In the present study, a wavelet-based methodology for automated seizure detection is presented. Twenty-one EEG recordings of 1-hour-long duration was initially segmented in 2 s epochs. Then, a 5-level-decomposition transform was applied in each segment using the 'db4' as mother wavelet. Five features namely, energy, entropy, mean of the absolute values of the wavelet coefficients, standard deviation and variance, were extracted in each subband of interest, creating the feature set that trained a SVM classifier. Seizure and non-seizure epochs were adequately classified and the obtained results are presented in Table 1.

Table 3 shows a comparison between the proposed method and other recent DWT-based methods that have been validated on Freiburg database. It can be seen, that this methodology shows really promising results in correctly identifying seizures. Average sensitivity is slightly lower than the one obtained in other approaches. However, this work has been tested only to a small part of the dataset, and more tests should be done to improve the method's performance.

Undoubtedly, epilepsy is a critical brain disorder that can lead to severe and life-threatening conditions, if left uncontrolled. The Freiburg database contains a large and comprehensive amount of data and further extensive study should be conducted. In the direction of developing robust seizure detection and prediction methods and personalized closed-loop treatment systems [19], different approaches, including the evaluation of various classifiers and the combination of linear and nonlinear features, should be examined.

Table 3 A comparison of performances of the various methods proposed in the literature for the detection of seizures using different data of the Freiburg database

Related studies	No. of patients/no. of analyzed seizures	Length (h)	Proposed method	Features	Classification problem	Sensitivity	Specificity	Accuracy
Liu et al. [12]	21/82	80.35	DWT	Relative energy, fluctuation index, coefficient of variation	Seizure/non-seizure	94.46	95.26	95.33
Zhou et al. [13]	21/81	289.14	DWT	Lacunarity and fluctuation index	Seizure/non-seizure	96.25	96.70	96.67
Xie et al. [14]	4/4	8	DWT	Wavelet variances	Ictal/interictal	–	–	99.00
Yuan et al. [15]	21/87	597.95	DWT	Diffusion distances	Seizure/non-seizure	95.11	98.78	98.77
Proposed method	21/21	20.57	DWT	Energy, entropy, mean, variance, standard deviation	Seizure/non-seizure	93.70	99.86	99.26

Conflict of Interest The authors declare that they have no conflict of interest.

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