EEG-Based Epileptic Seizures Detection with Adaptive Learning Capability

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Abstract: Epilepsy is considered one of the most common neurological disorders. Epileptic seizures can be a major life disability that might result in loss of consciousness, and/or injury to oneself or others. This research work aims to develop an epileptic seizure detection method using *electroencephalography* (EEG) signal analysis. We combine *discrete wavelet transform* (DWT), Shannon entropy, and statistical feature (standard deviation) to extract distinctive features of a given EEG signal. *Knearest neighbors* (KNN) automatically classifies the EEG signal by comparing the extracted features with the features of the normal and seizure baseline. Adaptive learning is used to continuously update the two baselines based the user feedback, if needed, to improve its performance over the time. Our proposed method achieved an overall 94.5 % sensitivity tested with up to 570 hours of continuous EEG recording from ten patients with total of 55 seizure events taken from CHB-MIT database. With its simplicity and fast processing time, the proposed method is suitable to be implemented in embedded device which has limited processing resource.

Keywords: seizure detection, adaptive learning, EEG, DWT, entropy, KNN.

1. Introduction

Epilepsy is known as brain disorder characterized mainly by recurrent and unpredictable seizures that interrupt normal brain function [1]. It is reported by International League Against Epilepsy (ILAE) commission that epilepsy affects more than 65 million people worldwide [2]. The development of an automated technique to detect seizure is very useful to improve the quality of life of epileptic patients. Seizure detection with a warning system is important for epileptic patients and their caregiver to prevent patient's injury because of involuntary responses due to the seizure.

Different modalities are used in the literature for seizure detection investigation such as *electroencephalogram* (EEG) [3-5], *electrocardiography* (ECG) [6-7], accelerometer [8-9] or the combination of them. However, EEG is considered the most common and reliable modality for epilepsy diagnosis and analysis. EEG provides large amount of brain information that is valuable for seizure detection [5]. The main processing steps for EEG-based seizure detection include: pre-processing, feature extraction and classification. Signal processing and machine learning techniques play important role for automatic analysis of EEG signals.

Recently, several promising EEG signal processing and feature extraction methods for seizure detection are proposed [10-23]. These methods could be further categorized into: time-domain (e.g, [10, 11]), frequency-domain (e.g, using filter bank [12] and sign periodogram transform [13]), time-frequency domain (e.g, wavelet transform [14-17]), nonlinear methods (e.g, using various entropies [18-19]) or combination of them (e.g, [10, 20]). Other methods include using spatial filter (e.g, common spatial filter [21]) and transforming EEG signal into 2D image (e.g, image texture analysis [22]). Different artificial intelligent and machine learning techniques are used also for EEG signal classification such as *artificial neural network*

Received: May 8th, 2017. Accepted: December 30th, 2017 DOI: 10.15676/ijeei.2017.9.4.13 (ANN) [11, 14, 16], support vector machines (SVM) [10, 12, 21-22] and k-nearest neighbor (KNN) [20].

EEG signal is generally non-stationary, nonlinear and complex. Therefore, applying only time-domain or frequency domain method to such type of signal is commonly unsuitable. Time-frequency analysis, such as discrete wavelet transform (DWT), is more suitable because it capture time and frequency properties of the signal simultaneously. DWT can represent the EEG signal in multiscale time-frequency domain and captures subtle changes in the signal. Due to the nonlinearity nature of EEG signal there is an increasing interest to use nonlinear method such as entropy for analyzing EEG signal. These motivate us to investigate combination of DWT (time-frequency method) and entropy (nonlinear method) to extract useful features from EEG signal.

Moreover, although some proposed seizure detection methods have achieved high accuracy (above 90%) several key issues still should be addressed. First, since seizure detection application is intended to be used by epileptic patient during daily life, it should not restrict the mobility and activity of the patient. Embedded system or mobile application is preferable; however in general it has limited processing resources that require simple method to be implemented. The selection of suitable type of EEG is also important. Several researchers designed and tested their seizure detector using intracranial EEG, e.g. [10, 13, 23]. Although intracranial EEG has better signal quality compare to scalp EEG but it is difficult to be used in normal life application because it need brain surgery to put the EEG electrodes. Scalp EEG is more practically to be used in normal life because it is noninvasive.

The second issue is about the adaptability. EEG signal is non-stationary that varies between subjects (epileptic patients) as well as varies depend on their mental conditions. Seizure detection method should be able to automatically adapt it properties to tackle this condition. However most of the proposed methods rely on extensive pre-training process for their machine learning algorithm (e.g., using ANN [11, 14, 16] or SVM [10, 12, 21-22]). Huge training data, both for normal EEG and EEG with seizures, are needed to obtain accurate Moreover, methods that relied only on pre-training would have poor seizure detector. performance for unseen data. For example, if a method was trained using EEG from a specific patient in a specific condition (e.g, during resting) it may not perform well for other patient or for the same patient but in different condition (e.g., during walking or talking). Clearly, any proposed method must not rely only on pre-training process, but also should have an adaptive learning capability to tackle variation in the EEG signals. The third issue related to the testing procedure. Many of the proposed methods, such in [17, 20-22], were tested only using selected EEG epochs (few minutes EEG segments), not continuous EEG recording. This testing scheme is less realistic and fails to provide some of the important detection performances such as false detection rate and latency.

In this study, we investigate seizure detection method with adaptive learning capability. With adaptive learning, a seizure detector system is able to reinforce new knowledge based on the user/patient feedback, if needed, to improve its performance over the time. Our proposed method based on combination of discrete wavelet transform (DWT) and Shannon entropy for feature extraction and k-nearest neighbors (KNN) for classification. Although various entropy functions are available for EEG analysis such as spectral entropy, approximate entropy, and sample entropy [18-19]; however Shannon entropy is much simple and faster to calculate. KNN is among the simplest classification methods and it did not relied on pre-training process. It may have adaptive capability by updating the baseline. We tested our proposed method using 570 hours continuous EEG recording form CHB-MIT scalp EEG database [24, 25]. Based on author based knowledge, there is limited prior study that investigated adaptive learning for seizure detection. In related topic, Wang et al [26], and followed by us [27], proposed an adaptive learning approach for seizure prediction. This paper is organized as follows. Section 2 describes the EEG dataset used in this work and also the proposed methods. Section 3 presents the results and discusses the important finding. The last section concludes the paper and highlights the future works.

2. Material and Methods

This section provides the detailed description about the EEG data and the proposed methods including feature extraction and classification methods. This section describes also the adaptive learning method to update the baseline.

A. EEG database

The database used to develop and test the proposed method is a 570 EEG recording hours of 10 different patients from CHB-MIT Scalp EEG database [24]. The data contain a total of 55 seizure events fully annotated by medical experts. The data is recorded using at least 23 EEG channels with sampling frequency of 256 Hz. More detailed description about this database is given in [25]. Figure 1 shows an example EEG record from the first patient that contains a seizure event. The seizure activity begins at around 2996 seconds. The EEG of an individual with epilepsy may exhibit abnormal rhythmic activity or discharges between seizures. Table I shows a summary of the data used in this study.



Figure 1. Example of EEG signals from CHB-MIT database

Patient	Gender	Age	N. of	Hours
			Seizures	(est.)
1	F	11	7	40
2	М	11	3	35
3	F	14	7	37
4	М	22	4	158
5	F	7	5	37
6	F	1.5	10	66
7	F	4.5	3	66
8	М	3.5	5	19
9	F	10	4	70
10	М	3	7	47
Total			55	575

	-		
Table I	Summary	z of the	FFG data
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The gender, age, number of seizures, and total hours of EEG recording for each patient are shown in the table. The EEG data is saved in several records (or files), each with one hour long for patients 1, 2, 3, 5, and 8; two hours for patient 10; and four hours for patient 4, 6, 7 and 9. The duration for each seizure varies between the patients, from tens of seconds until few minutes. Patient number six (infant) has the most seizure, but all of them are very short.

B. Overview of the Proposed Method

The proposed method is illustrated as shown in Figure 2. Firstly, a sliding window with a length N is applied to a continuous 23-channel EEG signals to obtain an EEG segment. Because EEG is non-stationary signal it is important to extract feature from small time EEG segment (epoch). The length (N) of the sliding window is fixed to 512 samples (equal to 2 seconds duration) for each channel. For feature extraction, discrete wavelet transform (DWT) decomposes the EEG segment into several EEG sub-bands, represented by different wavelet coefficients. Shannon entropy and standard deviation are calculated from each wavelet coefficients and the combined to construct feature vector. Based on the extracted features and the features of normal and seizure baseline, K-nearest neighbor (KNN) classifies the corresponding EEG segment into "normal" or "seizure" event.

The adaptive learning capability is achieved by automatically updating the feature baseline based on the user/patient feedback. The user may provide a feedback to the system whether the detection is "true" or "false". If the detection is false (the system make wrong detection), the system then automatically updates or adapts the feature baseline. The process is then repeated again for other EEG segment. The system is able to accumulate new knowledge through this adaptive learning to improve its performance over the time. The performance of the system is not depending on pre-training process.



Figure 2. Overview of the proposed method

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C. Feature Extraction

As mentioned earlier, combination of discrete wavelet transform (DWT), Shannon entropy, and statistical feature (standard deviation) are used to extract features from the EEG segment. DWT decompose EEG segment into several wavelet coefficients to capture time and frequency properties of the signal. Shannon entropy is then calculated from these coefficients as well as from original EEG segment to capture nonlinearity and regularity of the signal. The standard deviation is calculated also from the original EEG segment to represent statistical properties of the signal. The values of Shannon entropy (s) and standard deviation are then combined to construct the feature vector. More detailed explanation is described as follow.

DWT is able to capture the subtle changes in EEG signal by representing the signal into multiscale time-frequency domain in term of approximation and detail coefficients. Selecting the type of wavelet function and the suitable decomposition level for the DWT is crucial to capture meaningful information from the signal. In this work, we select *daubencies 4* (db4) wavelet because it is commonly used in the domain as described in the recent review paper focusing on wavelet for EEG analysis [28]. We have tried also other type of wavelet but the performance is not better than db4. The EEG signal is sampled at a sampling frequency of 256 Hz. The most useful information of any EEG signal is considered to be between 0-30 Hz spectrums [29]. Therefore, 6-level decomposition is selected for the DWT.

To obtain the first approximation A1[n] and detail D1[n] coefficients from a given EEG signal X[n], a pair of low pass g[h] and high pass h[n] filters are applied simultaneously to the signal.

$$A1[n] = (x * g)[n] = -\sum_{k=-\infty}^{\infty} x[k]g[n-k]$$
(1)

$$D1[n] = (x^*h)[n] = -\sum_{k=-\infty}^{\infty} x[k]h[n-k]$$
(2)



The formula for this pair of low pass and high pass filter is corresponding to the mother wavelet (in our case, *daubencies 4*). The next approximation and detail coefficients are calculated from the approximation coefficient obtained from the previous level. The complete

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output of 6-level DWT are given by D1 (128-256Hz), D2 (64-128Hz), D3 (32-64), D4 (16-32Hz), D5 (8-16Hz), D6 (4-8Hz) and A6 (0-4Hz). Figure 3 shows an example of EEG segment with its DWT outputs. Only D4, D5, D6 and A6 coefficients are used for the feature extraction to represent EEG sub-bands in the 0-32 Hz spectrums range. This is the well-known spectrum range in which EEG has useful information on it [29], as mentioned previously.

Entropy can be used to measure the complexity, regularity and the statistic quantification of time series data such as EEG. The abnormal nonlinearity and complexity in the brain signal may reveal brain condition or brain functionality. Shannon entropy is then calculated from these coefficients as well as from original EEG segment. Shannon entropy [30] measures the distribution of the data. For a discrete time series data $S[n] = [s_1 s_2 \dots s_N]$ with N is the length of the data, Shannon entropy (H) can be calculated as follows:

$$H = -\sum_{i=1}^{k} p_i \log_2 p_i \tag{3}$$

In which k is the number of distinct values in the discrete data (S) and p_i represents the probability or normalized frequency for these unique values. The standard deviation is calculated also from the original EEG segment. Standard deviation (SD) is calculated as follows:

$$SD = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (s_n - \mu)^2}$$
(4)

Where, μ is the mean of the discrete data. Six parameters (values) are extracted from each single-channel EEG segment as the features vector (five entropies and one standard deviation). In total, for a 23-channels EEG segment, 138 parameters are constructed as a feature vector. We did not perform normalization in the feature vector because KNN classifier is able to handle feature with different range values. Figure 4 shows an example of the entropy and standard deviation values extracted from 200 seconds EEG segment. Higher values (Shannon entropy above 8 and standard deviation above 100) indicates a seizure event. Seizure event occurs in the interval of 2996-3036s which can be distinguished from normal event by observing the entropy and the standard deviation values.



Figure 4. Entropy and standard deviation values from EEG signal

D. Classification with KNN

K-nearest neighbors (KNN) is among the simplest machine learning algorithm that classifies an object by the majority vote of its k nearest neighbors [31]. In this work, KNN is used to automatically classify the EEG signal by comparing the extracted features with normal and seizure baseline. It is important to choose the best value for parameter k to improve the classifier performance. The trade-off for selecting k is that a smaller value of k causes a

significant difference between classes, but the data would be sensitive to noise. In this work, k is considered to be equal to 3.

In the KNN classification, the object (EEG segment in this case) is classified based on the baseline. The size, initialization and updating of the baseline are crucial for classification. Generally, a bigger baseline size is more representative of the problem but it might be limited by the storage and the processing capability. Furthermore, the initialization of the baseline for each patient is done using the first EEG record of the training set that contains the seizure events. Figure 5 shows an example of normal and seizure baselines initialized using features extracted from the first EEG record with the seizure from the first patient. Note that each feature vector has 136 entries, only two are used in figure 5 for visualization. The size of normal and seizure baseline are not balanced, as such to be close to the real conditions (seizure event only happens periodically in a limited time).



Figure 5. Normal and seizure baseline for KNN classification

E. Adaptive Learning

The system is able to adapt or learn according to the user or the patient feedback to improve the seizure detector performance over the time (as illustrated in Figure 2). Machine learning techniques could be grouped into three classes: supervised learning, unsupervised learning, and reinforcement learning [26]. Adaptive learning is closely related to reinforcement learning in which the system reinforce new knowledge based on the online feedback or try and error, not by pre-defined training process. User feedback can work as a correction mechanism to help the system adapt to its properties (in our study, updating the feature baseline). This mechanism is very natural in real application. For example if the seizure detection is implemented in a mobile device, the user may just press a "wrong" button as a feedback when there is a false alarm from the device. Without adaptive learning, the feature baseline will be outdated cannot be used effectively for classification. We have tried to disable adaptive learning capability, we found the detection accuracy is very low, and especially there were too much false negative detection. The result of the seizure detection is either "normal" or "seizure" while the user feedback regarding this detection is either "true" or "false". Some possible outcomes of the seizure detections are as follows.

- *True Positive* (TP): seizure event detected as seizure event.
- True Negative (TN): normal event detected as normal event.
- False Positive (FP): seizure event detected as normal event.
- False Negative (FN): normal event detected as seizure event.

The baseline is updated according to the detections results. If the detection is true (both for true positive or true negative), no update is required. The baseline should be updated in the case of false detection, whether it was a false positive or a false negative. In the case of false positive, the seizure baseline would be updated, while in false negative the normal one is updated. There are several possible methods to update the baseline. Adding the new features under consideration to the baseline is used in the proposed technique. If the maximum baseline size is reached, then the new features are added by randomly removing the old ones. In this study, the maximum baseline is limited to 8000 feature vectors to have enough representation of the EEG signal. This baseline size is corresponding to 8000x2s=16000 seconds or 4.44 hours EEG recording. In practical, the baseline can be made as large as storage/processing capacity permitted to have diverse feature representations (from both normal and seizure EEG). Since KNN is a type of instance-based learning, it does not have an explicit training process. The "training step" is defined as the duration in which the classifier sequentially adapts its baseline in accordance with series of training data.

F. Performance Evaluation

The sensitivity, latency, and specificity are used to evaluate the proposed method [12]. The sensitivity is measured as the percentage of test seizures detected correctly by the detector. The latency is considered as the delay between the detection and the actual seizure onset. Specificity is referred to the false detection rate over 24 hour. We also use *leave-one-record-out* as a cross-validation method.

To calculate the sensitivity and latency of the detector, one seizure record is taken as testing data, while the rest (remaining seizure records plus all normal records) are used for training. This process is repeated until all seizure records are exactly used as testing data at least once. One normal record is taken as testing data, while the rest (remaining normal records plus all seizure records) are used for training to calculate the specificity (false detection rate). This process is repeated until every normal record is exactly used as testing data at least once. Then the false detection rate over the 24 hours is calculated.

3. Results and Discussion

In this work, we tested our classifier as *a patient-specific classifier* in which the training and testing are conducted on the data for each individual patient. The performance is then calculated by averaging all results. Another approach is to evaluate as *a patient non-specific classifier* by combining the whole data as a single data set for training and testing. The KNN parameter is selected to be k=3 in all experiments. Moving average m=3 is used to decrease the false detection rate for the smoothing the classifier output. Consequently, the actual detection decision in decided by the majority of the current classification output combined with the two previous outputs. The proposed method is able to detect correctly 52 seizures from a total of 55 seizure events (94.5% sensitivity) considering up to 570 hours of continuous EEG recording. The average detection latency is 8.3 second and false detection rate 27.4/24 hours. Figure 6 shows the number of detected seizures for each patient.



Figure 6. Number of detected seizures for each patient

As shown in the figure, the proposed method is able to detect all seizures for most of patients except patient number 6. Possible reason why the seizure detector fails to detect some seizures because the seizure duration is very short in patient 6, only around 12 seconds. In other patients the duration is longer (tens of seconds until few minutes), as mentioned before. Other possible reason is because this patient is still an infant (1.5 years old). The EEG signal is not strong enough; features during seizure are very similar to normal features for this patient. Table II shows a comparison of the proposed method with previous methods tested using the

same data, CHB-MIT database [24]. There are several other seizure detection methods such as [32-33] that have been tested using different dataset, namely University of Bonn dataset [34]. However, this dataset is very small and less comprehensive compare with CHB-MIT dataset. It should be mentioned also that some of the previous methods, e.g. [17, 20-22], are tested only using selected EEG segments (epochs) from the dataset and not the whole continuous EEG recording.

In general, our proposed method achieved promising results compared to other methods. Although the proposed method did not achieve the best performance for the given database, it has adaptive learning capability to improve its performance over the time and for different databases. The proposed method has the ability to update the baseline automatically for new unseen EEG data, therefore the seizure detector becoming more accurate and robust over the time. The proposed method has the advantage of simplicity. The adaptive learning capability is achieved by updating the baseline with simple adding or removing features based on the user/patient feedback. Shannon entropy basically employs only arithmetic and log operations.

Author (s)	Feature Extraction	Classifier	Data	Performance
Ali Shoeb		67 I) 6	Continuous EEG	SEN: 96%
<i>et al</i> [12]	Filter Bank	SVM	916 h, from 24	Latency: 3s
			cases	FDR (SPEC): 2/24h
S Nasehi			Continuous EEG	SEN: 98%
at al [16]	DWT, DFT	IPSONN	916 h, 24 cases	Latency: 3s
				FDR: 3/24h
Khan	DWT, energy,	IDA	Selected segments	SEN: 85%
<i>et al</i> [17]	NCOV	LDA	(epochs), 5 cases	SPEC: 100%
P. Fergus	C 1 f +	IZNINI	Selected segments,	SEN: 88%
<i>et al</i> [20]	Several leatures	KININ	24 cases	SPEC: 88.2%
Alotaiby	CGD	SAM	Selected segments,	SEN: 87%
<i>et al</i> [21]	CSP	5 v M	9 cases	SPEC: 93.2%
K. Samiee	Image texture	CAN	Selected segments,	SEN: 70.2%
<i>et al</i> [22]	analysis	5 V IVI	24 cases	SPEC: 97.4%
		KNN	Continuous EEG	SEN: 04 50/
This work	DWT, Shannon entropy, Std	(with adaptive	570h, 10 cases	SEIN. 94.5%
				Latency: 8.6s
		learning)		FDK: 27.4/24h

Table 2. Several EEG-based seizure detection

MATLAB R2009b is used to implement the proposed method, running on windows 7 PC with Intel i7 core @2.80GHz processor. The average processing time for DWT, Shannon entropy and standard deviation from single channel EEG segment (512 samples) are 0.13, 0.48 and 0.89 ms (millisecond) respectively. On average, the total time for a 23-channel EEG segment feature extraction is 110.6 ms, while for KNN classification is only 3-5 ms. The processing time for updating the baseline is negligible because it only adding or replacing baseline feature with already extracted feature from the current moving window. It is difficult to compare the processing time precisely because most of other works did not provide information about their processing time.

4. Conclusions and Future Works

In this paper, we have proposed automatic epileptic seizure detection with adaptive learning capability. The proposed method shows promising results tested using CHB-MIT dataset. It achieved an overall of 94.5 % accuracy tested using up to 570 hours of continuous EEG recording with very fast processing time as well. The future direction for the research work includes implementing the proposed method into FPGA or other embedded system. Several possible methods for updating the baseline will also be investigated. We consider also investigating seizure prediction, e.g. [27, 35], that not only recognizes the seizure while it occurs or in "onset", but also tries to predict before it occurs.

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6. Conflict of Interest

All authors declare there is no conflict of interest in any form.

7. References

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