A Novel Epileptic Seizure Detection Using Fast Potential-based Hierarchical Agglomerative Clustering Based on EMD

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Summary
Epilepsy is a chronic brain disorder that widely affects people. Mainly,it represents recurrent seizures that are brief episodes of involuntary movement. Detecting seizure is an important component in the diagnosis of epilepsy and for the seizures control. In the clinical practice, this detection basically involves visual scanning of Electroencephalogram (EEG).Many techniques have been developed for unscrambling the fundamental devices of the current seizures in EEGs. This paper presents a new framework using fast potential-based hierarchical agglomerative (PHA) Clustering Method and Empirical Mode Decomposition (EMD). The introduced algorithm first computes the Intrinsic Mode Functions (IMFs) of EEG signal, then calculates the Kolmogorov distance between each IMF and performs the detection based on PHA method. The evaluation results are very promising indicating an overall accuracy of 98.84%. A comparison between the proposed method and other existing methods in literature has been performed to show the advantage of proposed framework for detecting epileptic segments.

Key words:
Electroencephalogram (EEG), EMD, Epilepsy, PHA clustering, Seizure detection.

1. Introduction

Epilepsy results from brain underlying physiological abnormalities that affect people of all ages. Approximately, 70 million people worldwide suffer from epilepsy, making it the fourth most common neurological disorder [1].

Epilepsy is characterized by a sudden and recurrent malfunction of the brain, named “seizure”. Epileptic seizures are episodes that can vary from brief and nearly undetectable to long periods of vigorous shaking [2], [3]. The majority of the patients suffer from unpredictable, persistent and frequent seizures, which limit the independence of an individual and increase the risk of serious injury and mobility [4].The seizure detection is an important component in the diagnosis of epilepsy to figure out the causes, mechanisms and treatment. In the clinical practice, this detection involves visual scanning of Electroencephalogram (EEG) by the epileptologist in order to detect and classify the seizure activity present in the EEG signal [5]. However, Visual inspection is very time consuming and inefficient, especially in the case of long-term recordings. Thus, methods for automated seizure detection have gained considerable attention of the biomedical community researchers since the 1970s because they facilitate epilepsy diagnosis and enhance the management of EEG recordings.The selection of features that describe the behavior of EEG signals is a crucial stage for seizure detection and to get a best classifier performance. That's why several types of features selection have been proposed [6], including those based on time-domain [7], frequency domain [8],time frequency analysis[9],chaotic features [10] ,wavelet features [11] and the energy distribution in the time frequency plane [9]. Other detectors have utilized a combination of one or more than one technique. To improve their efficiency, these features have been tested using more than one classifier.

Minasayan et al have used the amplitude feature and combined it with other parameters to construct an input vector to an artificial neural network (ANN) [12].Du et al have proposed high order spectra (HOP) combined with principal component analysis (PCA) for the classification of epilepsy, achieving detection accuracies over 95% [13].Tzalas et al have applied the Wigner-Ville distribution (WVD) to selected segment of EEG signals and extracted several features, these features are fed into feed-forward ANN [14]. Samaneh Kazemifar, Reza Boostani have applied several time-frequency transforms to segment the EEG signals. The KPCA, full-rank KPCA and low-rank KPCA have been used to reduce the complexity and augment the accuracy rate, the projected features construct an input vector to (ANN) classifier[15]. Wilson et al have developed a commercial seizure detection algorithm Reveal based on matching pursuit technique. To speed the time running, they have used a wavelet package as atoms instead of Gabor atoms. The obtained features have been clustered using ANN rules [16]. Acharya et al have extracted recurrence quantification analysis parameters in

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order to classify EEG signals into interictal ,ictal and normal classes using recurrence plots of EEG signals; they have obtained a good classification accuracy[17].Yuan et al have used both approximate entropy (ApEn) and Hurst-exponent-Like features as inputs to classifiers based on ANN and support vector machine (SVM) [18]. Shoeb have presented a patient-specific seizure-onset detection algorithm, it extracts the eight features from 0-25HZ frequency band using a 3 HZ bandwidth filter and SVM classifier is used to classify the feature vectors [19]. To detect seizures and epilepsy, Adeli and Ghosh-Dastidar have applied a Wavelet-chaos methodology for analysis EEGs and EEG sub-band [20]. De Vos et al have proposed a three-way array tensor of EEG signal and developed a method using canonical decomposition to localize the epileptic seizure [21]. Also, Wavelet Transform (WT) has been widely used for detecting epilepsy. Meier et al have used WT combined with time features as an input for SVM classifier [7]. Khan et al have used relative energy and a normalized coefficient of variation (NCOV) as features for SVM classifier to detect seizure in paediatric patients [22]. Abibullaev et al have tested various wavelet functions to detect and extract the ictal epileptic seizure spikes [11]. Nasehi and Pourghassem have applied the DWT and DFT to extract the spectral features in five frequency bands. Then, an IPSONN classifier has been used to determine an optimal nonlinear decision boundary [23].
Recently, Empirical Mode Decomposition (EMD) has been employed for detecting epileptic seizure. Lorena Orosco et al have introduced an algorithm using EMD method. First, this method computes the Intrinsic Mode Functions (IMFs) of EEG records, then calculates the energy of each IMF and performs the detection based on an energy threshold and a minimum duration decision [24].B.Pushpa et D. Najumnissa have decomposed the epileptic seizure EEG signals using EMD, extracted the statistical features and classified seizure and normal EEG signals using back propagation artificial neural network (BPANN) and adaptive neuro fuzzy inference system (ANFIS) [25]. Shafiul Alam and Bhuiyan have developed a method by using higher order statistical moments of EEG signals such as skewness, variance, and kurtosis calculated in the empirical mode decomposition (EMD) domain. These moments have been employed as features to classify the EEG signals using an ANN [26]. Paschalis et al have introduced an epileptic seizure detection method based on time and frequency domain features selection from the Empirical Mode Decomposition (EMD) of EEG signals; these parameters have been used in a linear discriminant analysis (LDA) to classify epileptic seizure and normal EEG segments [27]. Bizopoulos et al have proposed an automated method for detecting epileptic seizures using an unsupervised method based on k-means clustering and Ensemble Empirical Decomposition (EEMD) [28].

This paper introduces a new framework based on EMD and PHA method to detect automatically the segments of the signals that represent epileptic seizures in EEG records. The first part of the presented methodology consists of using EMD to decompose EEG signal into a finite number of intrinsic mode functions (IMFs). These IMFs have been clustered with PHA method. Also, the Kolmogorov distance have been calculated between these IMFs and used as metric for the PHA algorithm. The flow diagram of the proposed system is shown in figure 1.
This paper is organized as follows: Section 2 is devoted to describe the proposed framework. In section 3, implementation results are presented. Finally, a concluding remarks and perspectives are given in section 4.

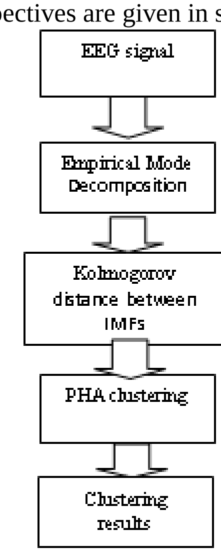

Fig. 1.Flow diagram of the proposed approach.

2. Methodology

2.1 Datasets

In this work, the online publicly CHB-MIT datasets available in phisionet.org have been used. This database, collected at the Children’s Hospital in Boston, consists of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. The EEG recordings that are divided among 24 cases, were collected from 22 subjects (5 males, ages 3–22; and 17 females, ages 1.5–19). (One patient has two sets of EEG recordings.). Case 24 was added to this collection in December 2010, and has no patient data. All signals were sampled at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (24 or 26 in a few cases). The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings. The data was segmented into one hour long records. Records that do not contain a seizure are called non-seizure records and those that contain one or more seizures are called seizure records [29].

2.2 Empirical Mode Decomposition

Empirical mode decomposition (EMD) was first proposed by Huang in 1998 [30], It has been applied in analyzing nonlinear and non- stationary signals, such as EEG signals [2],[5] .The EMD decomposes a signal into a finite number of Intrinsic Mode Functions (IMFs) with well defined instantaneous frequency. An IMF is defined as a function that satisfies following conditions [30] :

1. In the entire signal, the number of extrema and the number of zero crossings must either equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero.

The standard EMD algorithm was derived using following steps [30]:

1. Find all points of local maxima and all points of local minima of the signal $x(t)$.
2. Produce the upper envelope of local maxima and the lower envelope of minima $e_u(t)$ and $e_l(t)$, respectively.
3. Compute the mean of the mean of the upper and lower envelopes : $m(t) = (e_u(t) + e_l(t))/2$.
4. Extract the detail $d(t) = x(t) - m(t)$
5. Iterate steps 1-4 on the residual until the detail signal $d_k(t)$ can be considered an IMF (accomplish the two conditions): $c_1(t) = d_k(t)$
6. Iterate steps 1-5 on the residual $r_n(t) = x(t) - c_n(t)$ in order to obtain all the IMFs $c_1(t)$,... ,$c_N(t)$ of the signal.

The process is stopped when the final residual $r_N(t)$ is obtained as a monotonic function.

The result of the EMD process produces N IMFs ($c_1(t)$, …, $c_N(t)$) and a residue signal ($r_N(t)$),Hence, the original signal can be represented as:

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \qquad (1)$$

2.3 Fast Potential-based Hierarchical Agglomerative Clustering

Clustering methods are one of important steps used to separate segments that present epileptic seizure from normal segments in EEG data analysis. Seeking to find an efficient clustering algorithm with a high performance, we use the potential-based hierarchical agglomerative (PHA) clustering method [31]. This method can separate data into groups based on certain similarities. In [32], there are two kinds of clustering methods; partitional and hierarchical. However, PHA method is classified into hierarchical types which give a nested clustering result in the form of dendrogram, so that, several levels of partitions can be obtained. PHA method produced the potential field.

For two points i and j, if is the distance between them, the potential at point i from point j is given by the formula:

$$\emptyset_{i,j}(r_{i,j}) = \begin{cases} -\frac{1}{r_{i,j}} & if \quad r_{i,j} \geq \\ -\frac{1}{\delta} & if \quad r_{i,j} < \end{cases} \qquad (2)$$

Where is used to avoid the problem of singularity when becomes zero.

The total potential at point i is the sum of potentials from all the data points and described as follows:

$$\emptyset_i = \sum_{j=1..N} \emptyset_{i,j}(r \qquad (3)$$

Where N stands for the total data points.

In the f-PHA method, both the potential field produced by all the data points and the distance matrix are used to define a new similarity metric. In potential field model, different distances have being used such as Euclidian and Euclidian squared distance, which are not useful to find distance between time series. For that reason, we use in this work Kolmogorov as a distance between two IMFs.

Once the potential field model is constructed, PHA proceed to build edge weighted tree by using function to compute for each point the weighted and parent node. Finally these metrics are used to build dendrogram. For more details about PHA method, we invite the reader to see [31]. The f-PHA clustering algorithm is as follows:

PHA_Clustering (Dist[1..N,1..N] *{*
← the value computed from Dist[1..N,1..N]
(parent[1..N],weight[1..N])←
Build_Edge_Weighted_Tree *(Dist[1..N,1..N],)*
(dendrogramRoot,dendrogramParent[1..2×N- 2])←
Build_Dendrogram*(parent[1..N], weight[1..N])*
Rturn *(dendrogramRoot,dendrogramParent[1..2×N-2])*
}

The algorithm described above has time complexity O(N2) and allows to choose a max number of clusters , denoted as (k). However, generating automatically a number of clusters which is less than or equal to the selected max number (k) is delt by using function CLUSTER provided in Matlab. The CLUSTER Constructs clusters from a hierarchical cluster tree.

2.4 Performance Evaluation Parameters

In order to evaluate the performance of our approach the following statistical measures were used [33] [34]:

1. True Positive (TP)—The PHA identifies a segment that was labelled as a seizure by the neurologist.
2. True Negative (TN)—The PHA and the neurologist both agree that the EEG segment is normal.
3. False Positive (FP)—The PHA detects a seizure in an EEG segment that was labelled normal by the neurologist.
4. False Negative (FN)—The PHA has missed a seizure that the neurologist has identified in the segments.

Sensitivity is the capacity to find segments with seizure among real segments with seizure, it is expressed in percentage and defines the proportion of true positive segments with the seizure in a total group of segments with the seizure (TP/TP+FN). Complementary to sensitivity, specificity is the capacity to find segments without seizure among real segments without seizure, and it is the ratio of TN decisions to actual negative cases (TN+FP). Accuracy or effectiveness is expressed as a proportion of correctly classified segments (TP+TN) among all segments (TP+TN+FP+FN).

3. Experimental Results and Discution

Main steps of the proposed framework include applying EMD on EEG signals to obtain IMFs then performing the detection using the PHA clustering. The experiments are run on a desktop computer with an Intel Dual-Core CPU 2.40 GHz and 4 Go of RAM. In this work, MATLAB 2013a was used as the computation tool, the matlab codes for EMD are available at [35] and the PHA code is available at [36].

To estimate our framework‘s performance, Statistical parameters have been calculated. Figure 2 shows the sensitivity with which the framework detects the segments seizures of each of the 24 cases; the resulting 100 % sensitivity shows the correct identification of all epileptic segments. Figure 3 illustrates the number of segments without seizure of every cases declared by our approach, 98.58 % specificity shows adequate clustering by not recognizing the normal segments as epileptic segments . Figure 4 shows the percentage of the accuracy for each of the cases, 98.84% accuracy achieved suggest successful identification of normal and epileptic segments.

Fig. 2.Illustrates sensitivity of each of the 24 cases

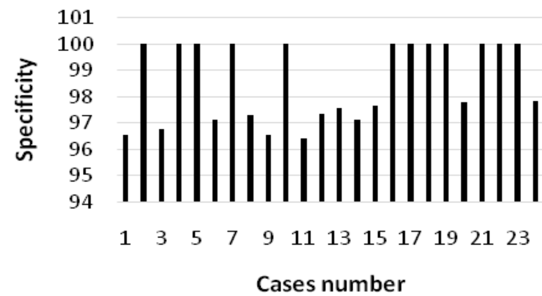

Fig. 3. Illustrates Specificity of each of the 24 cases

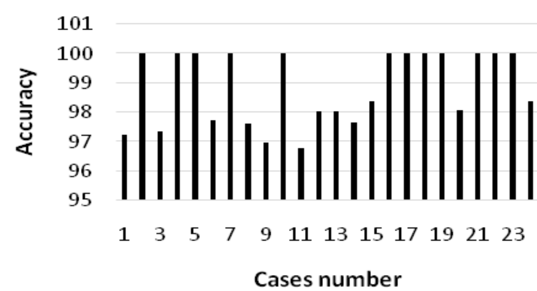

Fig. 4. Illustrates Accuracy of each of the 24 cases

Comparing our results with other existing studies using the same dataset, our approach produced better overall results. We find that Shoeb [19] produced a sensitivity value 96%, in a similar study, Nasehi and Pourghassem [23] used a neural network and reported a sensitivity value of 98%, which again is lower than the results reported in this study. For instance, Khan et al. [22] report an 83% Sensitivity, 92% accuracy and 100% specificity which is higher than our result (98.85).

4. Conclusion

The mean goal of this work is to detect automatically in EEG records those segments of the signal that present epileptic seizures for the shake of reducing the high amount of information to be analyzed by the neurologists. For that, we have proposed a new framework based on

Empirical Mode Decomposition (EMD) and PHA clustering approach. The results obtained shows that proposed framework are effective to represent the behavior of epileptic seizure EEG signals giving excellent clustering performance. It is observed that the proposed PHA can usually produce more satisfying results in terms of accuracy parameter, which makes it promising tool for epileptic seizure detection in EEG records and improve the clinical service of Neurologists. In future work this method can be evaluated using the other existing datasets and can also be enhanced by including a large database

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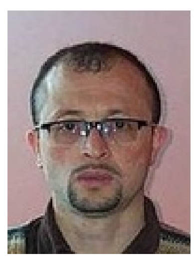

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