31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

An Epileptic Seizures Detection Algorithm based on the Empirical Mode Decomposition of EEG

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Abstract— **Epilepsy is a neurological disorder that affects around 50 million people worldwide. The seizure detection is an important component in the diagnosis of epilepsy. In this study, the Empirical Mode Decomposition (EMD) method was proposed on the development of an automatic epileptic seizure detection algorithm. The algorithm first 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. The algorithm was tested in 9 invasive EEG records provided and validated by the Epilepsy Center of the University Hospital of Freiburg. In 90 segments analyzed (39 with epileptic seizures) the sensitivity and specificity obtained with the method were of 56.41% and 75.86% respectively. It could be concluded that EMD is a promissory method for epileptic seizure detection in EEG records.**

I. Introduction

EPILEPSY is a chronic neurological disorder that affects around 50 million people worldwide of all ages [1]. This brain disorder is characterized by recurrent seizures which are the clinical manifestations of sudden, usually brief, excessive electrical discharges in a group of brain cells. Different parts of the brain can be the source of such discharges. Epilepsy responds to antiepileptic drugs about 70% of the cases and the remaining affected individuals could benefit from surgical therapy [1].

The seizure detection is an important component in the diagnosis of epilepsy. This includes visual scanning of Electroencephalogram (EEG) long recordings which is very time consuming and the conclusions are very subjective so disagreement between physicians are not rare. For this reason, the computerized analysis of EEG signals using automatic algorithms is highly useful for the diagnosis of this disease.

Several individual processing techniques and also a combination of those were employed and refined for epileptic seizures detection, quantification and recognition [2]. Neural Networks (NN) have been used to detect abnormal patterns in the EEG [3] and to identify seizure or preseizure states [4]. Wavelet Transform is also widely used for epilepsy detection [4], [5]. Others studies combine Approximate Entropy and Lempel-Ziv Complexity [6], and Time Frequency Distributions and NN [7].

In the last years, a new technique called empirical mode decomposition (EMD) has been proposed for the analysis of non-linear and non-stationary series. The EMD technique decomposed a series set into a finite and often small number of intrinsic mode functions (IMF) that admit well-behaved Hilbert transforms [8]. In the field of biomedical signal processing, EMD has been used for the analysis of respiratory mechanomyographic signals [9], for denoising in ECG records [10], and for tracking alpha rhythm in EEG recordings [11] and recently for epileptic seizure detection in EEG signals [12].

In this paper an epileptic seizure detection method based on EMD of EEG signal is proposed. The method computes the different IMFs of the signals and the seizure is detected applying energy and duration criteria on these IMFs.

II. Materials

The EEG database contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data were recorded during invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany [13]. In order to obtain a high signal-to-noise ratio, fewer artifacts, and to record directly from focal areas, intracranial grid-, strip-, and depth-electrodes were used. The EEG data were acquired using a Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16 bits A/D converter. Notch or band pass filters have not been applied in the acquisition stage.

The available EEG records include only 6 channels (3 focal electrodes and 3 extrafocal electrodes). The records are divided into segments of 1hour long. In this study, the 3 intra source records of 9 patients with focal epilepsy originated in the temporal lobe region were selected. This computes a total of 90 segments per each channel, 51 of them without epileptic seizures and 39 segments denoted as having only one epileptic seizure each.

This work has been supported by grants from Agencia Nacional de Promoción Científica y Tecnológica (PICT 2006-01689) and Universidad Nacional de San Juan, both institutions from Argentina, and by Ministerio de Ciencia e Innovación de España (TEC2007-68076-C02-01). The first author is supported by ANCYT, whereas the second and third authors are supported by CONICET of Argentina.

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III. METHODS

The proposed algorithm could be divided in the preprocessing stage, the EMD calculation step, the energy computation and the seizure detection phase. A block diagram of the seizure detection algorithm is illustrated in Fig. 1.

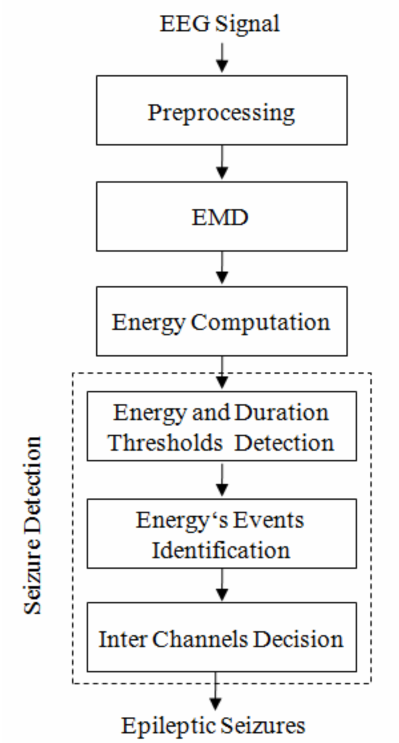

Fig. 1. Block diagram of the epileptic seizure detection algorithm.

A. Preprocessing

All EEG records were initially filtered with a second order, bidirectional, Butterworth, 50 Hz notch filter in order to remove the line frequency interference. Then, the EEG signals were band pass filtered with a second order, bidirectional Butterworth filter with a bandwidth of 0.5 - 60 Hz.

B. Empirical Mode Decomposition (EMD)

The EMD is a general nonlinear non-stationary signal decomposition method. The aim of the EMD is to decompose the signal into a sum of Intrinsic Mode Functions (IMFs). An IMF is defined as a function that satisfies two conditions [8]:

1. In the entire signal, the number of extrema and the number of zero crossings must be 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 (or close to zero).

The major advantage of the EMD is that the IMFs are derived directly from the signal itself and does not require any a priori known basis. Hence the analysis is adaptive, in contrast to Fourier or Wavelet analysis, where the signal is decomposed in a linear combination of predefined basis functions.

Given a signal $x(t)$, the algorithm of the EMD can be summarized as follows [8]:

1. Find local maxima and minima of $d_0(t)=x(t)$.
2. Interpolate between the maxima and minima in order to obtain the upper and lower envelopes $e_u(t)$ and $e_l(t)$, respectively.
3. Compute the mean of the envelopes $m(t)=(e_u(t)+ e_l(t))/2$.
4. Extract the detail $d_1(t)= d_0(t)-m(t)$
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 procedure terminates when the residual $c_N(t)$ is either a constant, a monotonic slope, or a function with only one extrema

The result of the EMD process produces N IMFs ($c_1(t)$, ..., $c_N(t)$) and a residue signal ($r_N(t)$):

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

The lower order IMFs capture fast oscillation modes of the signal, while the higher order IMFs capture the slow oscillation modes.

In this work, all EEG records were resampled to 128 Hz in order to reduce computation time of EMD decomposition. This operation does not have any influence on the results since the bandwidth of the signal of interest does not exceed the 60 Hz.

Then, IMF1 to IMF5 were calculated for every EEG segments of each channel. After several initial tests it was concluded that IMF4 and IMF5 do not contributed to seizure detection, so they were discarded. Only IMF1, IMF2 and IMF3 of EEG signals were used in further analysis. Fig. 2 shows the first 3 IMFs obtained with the described EMD method applied on an EEG segment with an epileptic seizure corresponding to patient 2, segment 15, channel 1.

C. Energy Computation

Once the IMF1, IMF2 and IMF3 were computed for all segments of each channel, the energy (ENi) of each IMFi was calculated as shown in (2)

$$ENi(n) = \frac{1}{L}\sqrt{\sum_{m=n-L/2}^{n+L/2-1}(IMFi(m))^2} \quad i = 1, 2, 3 \tag{2}$$

where i denotes the i-th IMF, n is its sample number and L is the length in samples for the energy computing window. In this work a 15 s window (L=1920 samples) were used.

After energy computation, three energy series (EN1, EN2 and EN3) corresponding to three IMFs were obtained. In Fig. 3 the energy of the IMFs of Fig. 2 are shown.

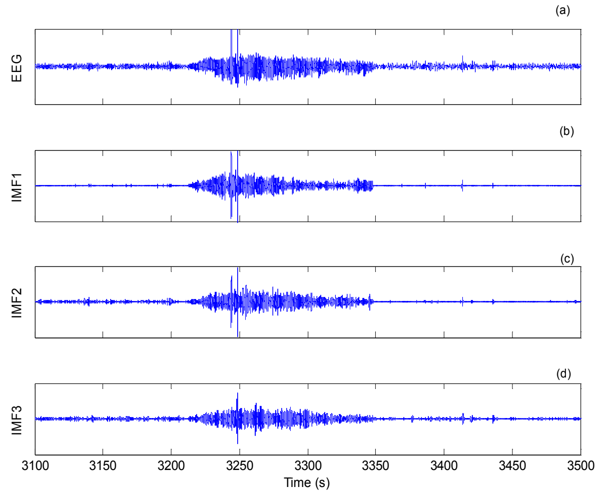

Fig. 2. (a) EEG signal with an epileptic seizure corresponding to patient 2 segment 15 channel 1, (b) – (d) IMF1, IMF2 and IMF3 of the EEG signal, respectively.

D. Seizure Detection Method

For seizure detection three decision stages are carried out as it is illustrated in Fig.1. The initial one is based on energy and duration thresholds detection and its output is defined as *events*. This step is made for each energy series of each channel. The *events* are the energy signal portions that overcome a threshold, computed as Thr_EN_i = mean (EN_i) + 1.5*std (EN_i), and last more than 30 s. The choice of this threshold was made after several tests since this option obtained the best results. By the other hand, the time period of 30 seconds was selected taking account that this period is the smallest duration of a temporal epileptic seizure [14].

The second decision stage is identifying those *events* present in at least two of the three ENs of each channel. This criterion is used in order to discard possible artifacts that could be present in only one EN*i*.

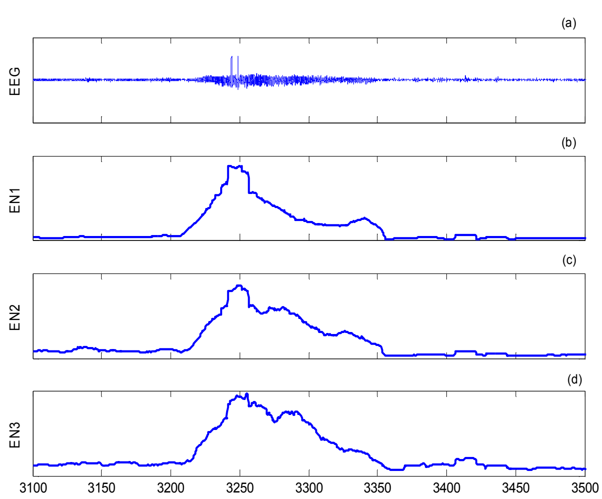

Fig. 3. (a) EEG signal with an epileptic seizure corresponding to patient 2 segment 15 channel 1, (b) – (d) EN1, EN2 and EN3of the IMFs (shown in Fig. 2) of the EEG signal.

Finally, in a third step an inter channel decision is done by choosing the events (elected in the previous stage for each channel) that are present in at least two of the three studied channels. The *events* that satisfy the three decision stages are considered as *epileptic seizure*.

IV. Results

The seizure detection algorithm was applied to a total of 90 EEG segments with 39 epileptic seizures, corresponding to 9 patients of Freiburg's data base with focal epilepsy originated in the temporal lobe region.

In order to evaluate the performance of the method the following diagnostic categories were considered on the detection stage: true negative (TN), false positive (FP), true positive (TP), false negative (FN). These indexes are shown quantitatively for each patient in Table I.

TABLE I
Freiburg's Data Base Diagnostic Values

ID Patient	TN	FP	TP	FN
2	3		3	
4	4	5	3	2
7	3		2	1
10	2	4		5
12	3	2	4	
15	6		3	1
16	6	2	1	4
17	10	1	5	
21	7		1	4
Total	44	14	22	17

TN = True Negatives, FP = False Positives, TP = True Positives, FN = False Negatives.

The statistical diagnostic indexes of false detections (FD), sensitivity, specificity, positive predictive value, negative predictive value and error rate detection were also computing [15]. These indexes are defined as follows:

Sensitivity (SEN): Is the proportion of epileptic seizures correctly detected by the algorithm.

$$SEN(\%) = \frac{TP}{TP + FN} \times 100 \tag{3}$$

Specificity (SPE): Is the proportion of segments without seizures correctly identified by the algorithm.

$$SPE(\%) = \frac{TN}{TN + FP} \times 100 \tag{4}$$

Positive Predictive Value (PPV): Is the fraction of segments with epileptic seizures correctly detected by the algorithm.

$$VPP(\%) = \frac{TP}{TP + FP} \times 100 \tag{5}$$

Negative Predictive Value (NPV): Is the fraction of segments without epileptic seizures correctly detected by the algorithm.

$$NPV(\%) = \frac{TN}{TN + FN} \times 100 \tag{6}$$

Error Rate Detection (ERD): Is the relation between the false detections and the total segments with epileptic seizures.

$$ERD(\%) = \frac{FP + FN}{TP + FN} \times 100 \tag{7}$$

These parameters calculated for each patient are shown in Table II. The indexes values for the total of the studied patients can be seen in the last row of Table II.

V. Discussion and Conclusions

In this work, an automatic epileptic seizure detection algorithm based on Emipirical Mode Decomposition (EMD) of EEG signals has been proposed.

The algorithm was tested in 90 EEG segments acquired in 9 patients with focal epilepsy originated in the temporal lobe region. The global specificity for the algorithm is 75.86% which indicates that the algorithm is good in correctly classify the EEG segments without seizure. In the other hand, the sensitivity of 56.41% indicates that the developed method could classifies only a little more of the half of epileptic seizures analyzed. A possible cause of this low sensitivity could be the use of a fixed threshold in the detection stage. The positive and negative predictive values reach in the method are 61.11% and 72.13%, respectively.

It was also observed that the computation time of EMD for each segment is quite extensive which could represent a disadvantage for analyzing long EEG records.

It could be concluded that EMD is a promissory method for epileptic seizure detection in EEG records. Nevertheless, more tests and some adjustments on the algorithm must be made in order to be suitable for medical diagnosis.

As future extension of this research the algorithm will be tested in the EEG records of the remaining patients of the Freiburg's database. Also, other detection schemes based on EMD technique will be examined in order to increase the sensitivity of the proposed method. The implementation of more adaptive thresholds and neural networks will be made to improve the performance of the method.

Acknowledgment

The authors are very grateful to the Epilepsy Center of the University Hospital of Freiburg, Germany, for their consent to use the invasive EEG recordings in this work.

TABLE II
Statistical Diagnostic Indexes for each Patient and for the total of it

ID Patient	FD	SEN (%)	SPE (%)	PPV (%)	NPV (%)	ERD (%)
2	0	100	100	100	100	0.00
4	7	60.00	44.44	37.50	66.67	140
7	1	66.67	100	100	75.00	33.33
10	9	0.00	33.33	0.00	28.57	180
12	2	100	60.00	66.67	100	50.00
15	1	75.00	100	100	85.71	25.00
16	6	20.00	75.00	33.33	60.00	120
17	1	100	90.91	83.33	100	20.00
21	4	20.00	100	100	63.64	80.00
Total	31	56.41	75.86	61.11	72.13	79,49

FD = False Detections, SEN = Sensitivity, SPE = Specificity, PPV = Positive Predictive Value, NPV = Negative Predictive Value, ERD =Error Rate Detection

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