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An Energy-Based Detection Algorithm of Epileptic Seizures in EEG Records

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***Abstract*— A simple algorithm to automatically detect segments with epileptic seizures in long EEG records has been developed. The main advantages of the proposed method are: the simple algorithm used and the lower computational cost. The algorithm measures the energy of each EEG channel by a sliding window and calculates some features of each patient signal to detect the epileptic seizure. It is also able to distinguish between seizures and noise artifacts. Nine invasive EEG records acquired by Epilepsy Center of the University Hospital of Freiburg were analyzed in this work. In 90 segments studied (39 with epileptic seizures) the sensitivity obtained with the method is 87.18 %. The algorithm is appropriate to detect epileptic seizures, with high sensitivity, in long EEG records to decrease the time used by physicians and specialists in visual inspections.**

I. Introduction

EPILEPSY is a chronic neurological disorder that affects people of all ages worldwide [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.

It is accepted that 0, 5-1, 5% of the world population suffers epilepsy (n = 60 millions approximately) [1]. The electroencephalogram (EEG) is the standard technique for investigating the brain electrical activity in different physiological and pathological states. Fig 1 shows a 200 s segment of an EEG record with an epileptic seizure. When an epileptic focal seizure is generated, synchronized epileptic brain activity is initially observed in a small area of the brain. From this focus, the activity spreads to other brain areas [2]. This process is reflected in the EEG records, visual inspection of the EEG data is usually done by physicians and specialists, but it is a hard work when long records are inspected.

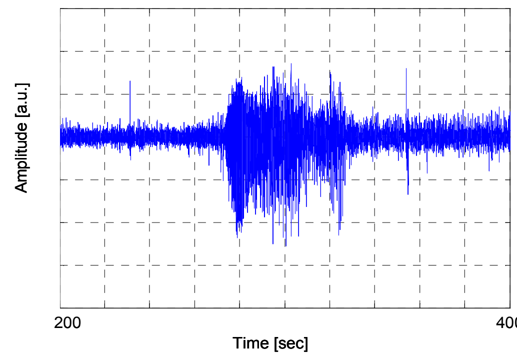

Figure 1. EEG record with epileptic seizures.

Many authors have developed techniques to automatically detect epileptic seizures in EEG records [3]. For this purpose, different Neural Networks have been used combined with ICA [4] Wavelet Transform *(WT)* [5,6], Approximate Entropy *(ApEn)* and Lempel-Ziv Complexity *(LZ)* [7], Empirical Mode Decomposition *(EMD)* [8], among others. Most of these algorithms required a high computational cost to detect and classify epileptic seizures, so the automatic analysis of long EEG records (24, 48, 72 hours or more) is very slowly and complicated. The discussion of those methods is included in section V.

A simple algorithm to detect automatically segments with epileptic seizures in EEG records has been developed in this work. The idea of this algorithm is not to replace the important ocular inspection of physicians and specialists but to give a tool to facilitate their work and to reduce the extended time that an ocular analysis of longs EEG records takes. An algorithm that gives marks in those places that need detail inspection is of great help. In pre-surgical medical examination of epilepsy invasive EEG records of the patient are taken without medication to detect and register one or more epileptic seizures during one or more days. To make data processing easier the records are normally divided in segments of 1 or 2 hours.

The algorithm measures the energy of each EEG segment by a sliding window and calculates some features of each patient signal to detect and classified epileptic seizure segment. The main advantages of the proposed algorithm are its simplicity and low computational cost, which made this appropriate to analyze more than 24 or 72 hours of EEG records.

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II. MATERIALS

The Freiburg 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 [9]. In order to obtain a high signal-to-noise ratio, with few artifacts, and to record directly from focal areas, intracranial grid-, strip-, and depth-electrodes were utilized. 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.

Nine of the twenty one records of the Freiburg Database were used in this work. These records correspond to patients with a epileptic focus located in the temporal lobe. In the database, there are only 6 EEG channels of the 128 available (3 focal electrodes: channels 1-3 and 3 extra focal electrodes: channels 4-6).

The EEG records are divided in segments of 1 hour duration. Each segment has been previously revised by physicians. Segments denoted as having seizures, have only one epileptic seizure.

III. METHODOLOGY

The proposed algorithm for epileptic seizures detection is based on determining the energy and the duration of certain features in each channel of EEG record. A block diagram of the proposed algorithm is illustrated in Fig.2.

The algorithm analyzes the energy values in each channel and made a multi-channel decision in the complete records to determine the time position of the epileptic seizures.

A. Filtering

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.

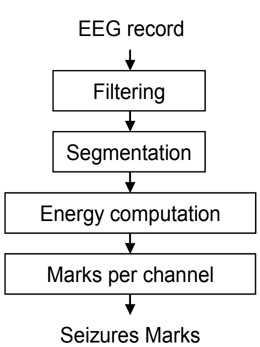

Figure 2. Block diagram of proposed algorithm for epileptic detection in EEG records.

B. Segmentation

For the analysis of the EEG records a segmentation of 2 seconds of duration was done. The reason for doing this is to assure statistical stationary. The duration of the blocks was chosen from best result after testing the algorithm with durations of 1, 2, 5 and 10 seconds

C. Energy computation

For each channel and segment of EEG record, a primary energy time series E1 is obtained, by calculating the energy of each 2s block of EEG signal with (1) and (2)

$$e_b = \sqrt{\frac{\sum_{i=1}^{N} x_i^2 \ln\left(x_i^2\right)}{N}} \qquad ;\forall x \neq 0 \tag{1}$$

$$E1 = \left[e_1, e_2, e_3, \ldots\ldots, e_b\right] \tag{2}$$

where i is the time sample, b are the 2s blocks and N = 512 samples.

Then a moving median filter of 7 points was used to smooth the signal and to eliminate those events with high energy and short duration corresponding to noises. The filtered energy series is called E2. Finally, a smoothing version of E2 is obtained using an average moving filter of 60 points, resulting the final energy series called E3.The detection series is called ZD (seizure detection).

Fig. 3.a and 4.a show the E1, E2, E3 and ZD series in an EEG segment with an epileptic seizure corresponding to segment #15 of patient #2, and in a segment with a noise artefact to segment #206 of patient #4.

D. Thresholding.

In order to detect the epileptic seizure, the maximum value of the E3 energy time series is compared with upper and lower thresholds (U_THR and L_THR, respectively) obtained from the median of the E3 energy time series (U_THR = 10 * median(E3_series) and L_THR = 1.5 * median(E3_series)). The maximum value must be between U_THR and L_THR. The thresholds are fixed for each channel, each segment and each patient. If the maximum value satisfies the previous condition, the ZD series (seizure detection) have positive values for a fixed time. The ZD series obtained in this stage can be observed in the lower row of Fig. 3a. The approximate initial endpoint of the epileptic seizure is estimated as the temporal position of the maximum value of the E3 energy time series. Its final endpoint is estimated as the temporal position in which the curve of E3 changes the slope from negative to positive (See E3 and ZD in Fig 3a).

E. Multi-channel decision

With the purpose of giving robustness to the algorithm, a multi-channel decision has been taken based on the fact that the epileptic seizures appear in more than one channel. Typically, the epileptic seizure is simultaneously reflected in all EEG channels near the focus. Additionally, an approach of time duration of the seizures is taken.

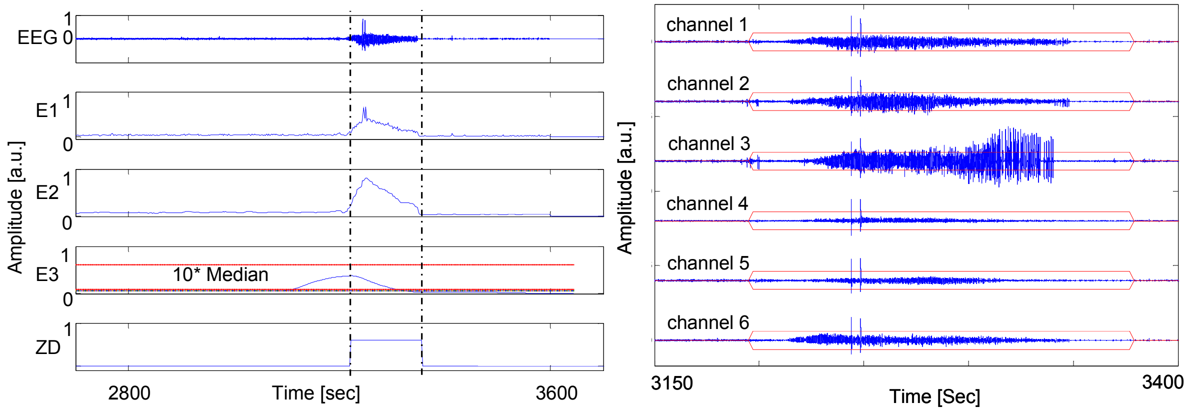

Figure 3. EEG Segment with epileptic seizure (Patient 2, segment 15)a) Focal Channel 1- EEG signal. E1, E2, E3 and seizure detection. b) All channels detection. Focal electrodes: channels 1-3 and extra focal electrodes: channels 4-6.

The upper and lower thresholds of temporal duration of the seizures [2] were defined, based on the typical duration of an epileptic seizure (between 30 and 180 seconds). The duration of the positive values of the ZD series is compared with those time thresholds.

The approach used is that the initial and final endpoints of at least two channels agree temporarily in a window of +/- 5 seconds of duration. If the analysis per channel one epileptic seizure is not detected in any channel or only in one channel, the multi-channel analysis considers that there is a not epileptic seizure in that record. Decisions are taken based on focal and extra focal electrodes.

Fig.3.a shows the marks of epileptic seizure for channel #1 of segment #15 of patient #2, whereas Fig. 3.b shows the seizure detection for all six EEG channels.

Fig.4.a shows the time series for this segment that does not reach the thresholds of duration of the seizures, so there was no detection. In fig 4.b, all channels are shown.

IV. Results

The quantitative analysis of the algorithm was done in 90 EEG segments (39 segments with epileptic seizures and 51 ones without seizures) corresponding to 9 patients with epilepsy of temporal lobe origin, from the validated database of Freiburg.

TABLE I
DETECTION CATEGORIES FOR EACH PATIENT

ID Patient	Number of segments	TP	TN	FP	FN
2	6	3	3		
4	10	5	4	1	
7	6	3	3		
10	11	2	4	2	3
12	8	4	3	1	
15	10	2	6		2
16	12	5	5	2	
17	15	5	10		
21	12	5	7		
Total	**90**	**34**	**45**	**6**	**5**

In order to evaluate the performance of the proposed algorithm, some statistical parameters have been calculated.

The results of classifying segments are divided in four detection categories: True Positive (TP the number of segments with epileptic seizures that the algorithm detect correctly), True Negative (TN number of segments without epileptic seizures that the algorithm recognize correctly), Positive False (FP number of segments without epileptic seizures that the algorithm detect erroneously as positive) and Negative False (FN number of segments with epileptic seizures that the algorithm doesn't detect). The results of these values are indicated in Table I for each analyzed patient. The total numbers of segments is TP+FP+TN+FN, of which TP+FN are segments with epileptic seizures.

The following statistical parameters were calculated to determine the performance of the algorithm: *False detections (FD), Sensitivity (Sen), Specificity (Spe), Predictive positive value (Vpp), Predictive negative value (Vpn), Rate of detection error (Err)* [10]. These values are shown in Table II, for each patient and in Table III considering all analyzed patients of the database.

TABLE II
STATISTICAL PARAMETERS FOR EACH PATIENT

ID Patient	FD	Sen (%)	Vpp (%)	Err (%)	Spe (%)	Vpn (%)
2	0	100.00	100.00	0.00	100.00	100.00
4	1	100.00	83.33	20.00	80.00	80.00
7	0	100.00	100.00	0.00	100.00	100.00
10	5	40.00	50.00	100.00	66.67	66.67
12	1	100.00	80.00	25.00	75.00	75.00
15	2	50.00	100.00	50.00	100.00	100.00
16	2	100.00	71.43	40.00	71.43	71.43
17	0	100.00	100.00	0.00	100.00	100.00
21	0	100.00	100.00	0.00	100.00	100.00

TABLE III
STATISTICAL PARAMETERS FOR THE TOTAL OF PATIENTS

FD	Sen (%)	Vpp (%)	Err (%)	Spe (%)	Vpn (%)
11	87.18	85.00	28.21	88.24	88.24

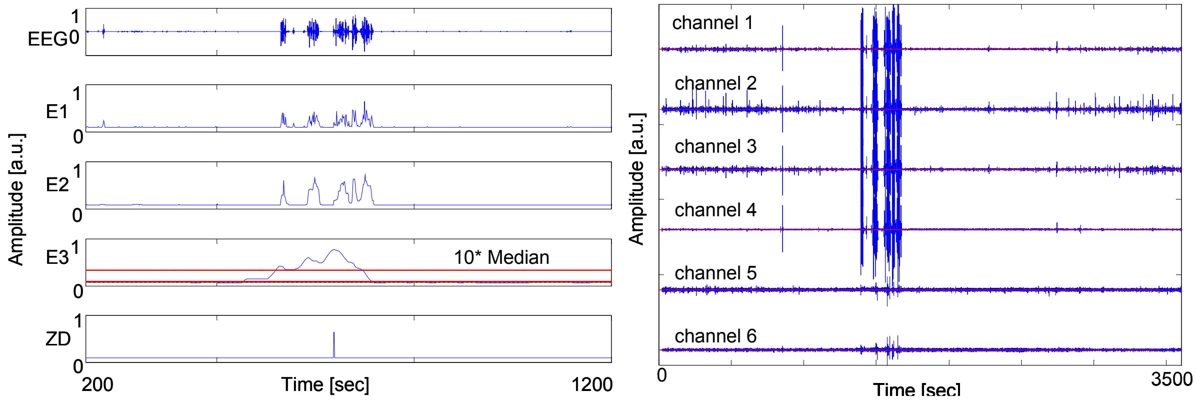

Figure 4. EEG Segment without epileptic seizure and corrupted with a noise artefact (Patient 4, segment 206). a) Channel 1- EEG signal. E1, E2, E3 and ZD, b) All channels Focal electrodes: channels 1-3 and extra focal electrodes: channels 4-6.

V. Discussion and Conclusions

The results obtained demonstrate that the proposed algorithm is a useful and simple method to detect epileptic seizures in long EEG records.

The results indicate that the proposed method has sensitivity higher than 87% for the epileptic seizures detection. A method used *EMD* and *WT* to detect epileptic seizures with the Freiburg database get sensitivity of 91% [8]. Other work using *ApEn* and *LZ* [7] find statistical differences in EEG records of the same database before, during and after epileptic seizure but do not classify them. However, the computational cost of *EMD, WT, ApEn* or *LZ* is higher than the proposed method, so it is simple and appropriate to detect seizures in long EEG records.

The specificity of the method is 88.24%. The positive and negatives predictive values reach 85.00% and 84.24%. It is important to point out that FN is much more problematic than FP in epileptic seizure detection. In table I it could be observed that 34 of 39 segments with seizures were correctly detected by the algorithm and the other 5 segments correspond to patients #10 and #15, where the epileptiform activities are not clear in their EEG records. Finally, the rate of detection error is in general of 28.21 %.

It has been concluded that the proposed method is appropriate to help physicians to detect the epileptic seizures in EEG records of long duration with positive results. It is a useful tool in case that the invasive EEG record last more than 24, 48 or 72 hs.

As future work, the algorithm will be examined in all the patients from the Freiburg database and the initial and final endpoints of the epileptic seizure will be calculated and compared with the marks provided by the physician in the database. Also, the algorithm will be tested in scalp EEG records which have lower SNR than the intracranial EEG records used in this work.

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References

[1] World Health Organization. Programmes and projects. Available: http://www.who.int/mediacentre/factsheets/fs999/en/index.html

[2] A. crespel, Gélisse P, et al., “Atlas of Electroencephalography”, 1st ed,. vol. 2, Ed. John Libbey Eurotext, Paris, 2005. ISBN 2-7420-0600-1.

[3] S. Sanei and J. Chambers, “EEG Signal Processing”, Willey, England, 2007. ISBN 978-0-470-02581-9.

[4] V. Golovko, S. Bezobrazova, S. Bezobrazov and U. Rubanau, “Application of Neural Networks to the Electroencephalogram Analysis for Epilepsy Detection,” Proc. of Int. Joint Conf. on Neural Networks, Orlando, Florida, USA, August 12-17, 2007.

[5] R Schuyler, A White, et al, “Epileptic Seizure Detection”, IEEE Engineering in medicine and Biology Magazine. Vol 26, no 2, March-April 2007 Page(s):74-81

[6] H. Adeli, S. Ghosh-Dastidar and N. Dadmehr, “A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subbands to Detect Seizure and Epilepsy,” IEEE Trans. On Biomed. Engineering, vol. 54, no. 2, Febraury 2007, pp 205-211.

[7] D. Abásolo, C. James and R. Hornero, “Non-linear Analysis of Intracranial Electroencephalogram Recordings with Approximate Entropy and Lempel-Ziv Complexity for Epileptic Seizure Detection,” Proc. of the 29th Annual Int. Conf. of the IEEE EMBS Cité Intern, Lyon, France August 23-26, 2007, pp. 1953-56.

[8] A Tafreshi, A nasrabadi, A Omidvarnia, “Epileptic Seizure Detection Using Empirical Mode Decomposition”. Signal Processing and Information Technology, 2008. ISSPIT 2008. IEEE International Symposium on16-19 Dec. 2008 Page(s):238 - 242

[9] Freiburg EEG Data Base. Available: https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database

[10] Altman D.G. Practical statistics for medical research. Chapman & Hall, London, Uk, 1993.