A mimicking approach for human epileptic seizure detection

B. Hunyadi, M. De Vos, W. Van Paesschen and S. Van Huffel

***Abstract*—The seizure detection algorithm presented here concentrates on the visually appearing characteristics, on which neurologists also rely when reading the EEG data. The main steps of the algorithm reformulates these characteristics as mathematical features: 1. analysis of signal power at different frequency bands; 2. identification of affected channels based on the asymmetry of contra-lateral channel pairs; 3. extraction of spike segments; 4. retrieval of a series of repetitive spikes with gradually evolving amplitude. The results of detection can be compromised by artifacts contaminating seizure pattern or causing false detections. It will be shown how to overcome the difficulties posed by different artifacts, with special attention to muscle artifact removal. The sensitivity of the proposed algorithm is 84% together with a false detection rate of 0.24/h.**

***Index Terms*—epilepsy, seizure detection**

I. Introduction

Epilepsy is a neurological disorder, affecting 50 million people worldwide [1]. The manifestation of this disease is the epileptic seizure, an abnormal, synchronous activity of the neurons in the brain. More than 20% of epilepsy patients are non-responsive to medication [2], hence their quality of life is seriously compromised. Surgical resection of the epileptogenic focus might offer cure for these patients. However, the success of the surgery strongly depends on the accurate identification of the brain region responsible for the generation of seizures. As the seizure spreads quickly through the brain, the early detection of the epileptic seizure is essential to reveal the source brain region. Injection of a radiopharmaceutical material soon after seizure onset facilitates an accurate localization of the epileptogenic focus on an ictal SPECT scan. To be on alert for clinical symptoms is insufficient as they may arise later on in the course of a seizure. Moreover, subclinical seizures are completely omitted this way. EEG monitoring is a useful technique for providing information about seizures, including the precise onset time, due to its fine temporal resolution. Continous visual observation of EEG signals is also impractical. Alternatively, a computer-based automatic seizure detector with onset alarm can be used.

Besides, EEG monitoring is used for diagnosis of epilepsy and follow-up after surgery. The objective in this case is to discover all occurent seizures. As the monitoring of one patient takes several days, the amount of data to be analyzed is huge. An automatic seizure detection technique would drastically decrease the work load of clinicians.

B.Hunyadi, M.De Vos and S. Van Huffel are with ESAT-SISTA, Department of Electrical Engineering, Katholieke Universiteit Leuven, Belgium

W. Van Paesschen is with University Hospital Gasthuisberg, Department of Neurology, Leuven, Belgium

The large variability of seizure characteristics and the variety of artifacts contaminating the EEG recordings present a great challenge to the developers of such an application. The requirements of a suitable seizure detection system is high sensitivity, high specificity, and low detection delay.

II. Materials and methods

A. EEG data

The seizure detection algorithm was developed based on a training EEG dataset containing surface recordings from 22 different patients with partial refractory epilepsy, who underwent presurgical evaluation. In total 32 seizures were recorded. The average duration of the recordings was 4.9 hours, resulting in a total of 108 hours EEG data.

B. Seizure detection algorithm

There are well defined characteristics of the EEG, on which the neurologist relies when determining whether the segment of the EEG recording under investigation contains seizure activity or not. The typical seizure pattern contains evolving, repetitive sharp waves. The evolution might be observed in frequency, amplitude, topography and morphology. Frequency evolution is a change in the frequency distribution of the signal, caused by an increased activity in a certain frequency band. Amplitude evolution means simply an increase in signal amplitude. The seizure is spreading towards new brain regions from the source during its course, resulting in the appearance of the seizure pattern on more and more EEG channels, changing the topography of the activity. Finally, the morphology of the signal is influenced by the gradual replacement of the background activity by the ictal pattern [3]. The above described visual characteristics can be reformulated as mathematical features and will serve as the consecutive steps of the seizure detection algorithm:

1) Preprocessing: The EEG data is broken down into 5s long single channel epochs. Each epoch is band pass filtered between 2-25Hz and a notch filter at 50Hz is applied. For the further analysis, the average referenced preprocessed epochs of single channels are used.

2) Energy and asymmetry: In this work we are focusing on the detection of the seizure as early as possible. The foremost peculiarities of the seizure onset are the change in signal energy distribution on a certain group of channels, associated to the primarily affected brain regions. The energy and asymmetry characteristics of the signal are investigated for four distinct frequency bands denoted by F: delta (2-4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-25Hz). The feature

corresponding to the signal energy is the ratio of the power spectral density (PSD) in the current epoch and frequency band to the PSD of the same band in the background EEG. PSD is computed according to Welch's method; background is defined as the 30s long recording preceding the current epoch:

$$PowRate(ch,F) = \frac{\sum_{f=F_{min}}^{F_{max}} PSD_{f,ch}}{\sum_{f=F_{min}}^{F_{max}} PSD_{f,ch,bgr}} \quad (1)$$

To exploit topographic information of the EEG pattern, brain symmetry index (BSI) is a useful tool. BSI was introduced to quantify the asymmetry in spectral power between the two hemispheres [4]. Here we modified the pairwise BSI defined in [5] to measure channel symmetry index (CSI) - the power asymmetry in the predefined bands between contralateral channels pairs:

$$CSI(ch,F) = \sum_{f=F_{min}}^{F_{max}} \frac{PSD_{f,ch} - PSD_{f,opp}}{PSD_{f,ch} + PSD_{f,opp}} \quad (2)$$

where $PSD_{f,ch}$ and $PSD_{f,opp}$ are the power spectral density of the actual channel and the contralateral channel, respectively, at frequency f, running from the lower F_{min} and upper F_{max} limits of the frequency band F. This formula points out which member of the channel pair exerts higher power in the current frequency band. Its value can vary between -1 and 1, a positive value meaning that channel ch exerts more power, a negative value meaning that the contralateral channel does.

In case of a focal or hemispheric seizure, a significant asymmetry can be observed between channel pairs. However, the asymmetry between the hemispheres are less expressed for of a generalized seizure. According to our observations the energy change of the signal is more significant in such a case. Consequently, the energy and asymmetry information of the actual epoch is combined into one parameter for threshold classification:

$$CSI(ch,F) \times (PowRate(ch,F) - 1) > T \quad (3)$$

The value of the combined parameter becomes negative if either the channel is non-dominant with respect to its pair, or if it exerts lower power than the background. A positive threshold T will certainly reject such segments, beside others segments with relatively low asymmetry (CSI) and energy change ($PowRate$). The threshold value is empirically set to 0.6. The frequency band F, for which the actual epoch survives the thresholding, is kept in the memory for the following step, and will be referred to as the determinative band of the epoch.

3) Wave extraction: The epochs selected as seizure candidates in the previous step are now broken down into consecutive wave segments. A similar procedure was used by Gotman in [6]. Waves are defined as segments of signal limited by the minimum amplitude samples found between adjacent zero-crossings of the oscillatory signal. The waves obtained might have a large variability in duration for a noisy channel, and the ones originating from irrelevant brain activity, artifacts or noise should be rejected. Only those waves are kept for further analysis, which correspond in duration to the determinative frequency band of the epoch, assigned according to (3).

4) Evolving repetitive wave sequence: As a first step each wave is compared to a spike template taken from a typical ictal activity pattern by visual inspection. If the summed mean square error of all the waves in the current epoch is sufficiently small, the algorithm proceeds and searches for a wave sequence evolving in amplitude. A new wave is added to the existing sequence if its amplitude is at least 90% of the amplitude of the preceding wave, and the mean amplitude of the total wave sequence does not decrease. The resulting sequence might not contain consecutive waves anymore, skipping segments of data affected by noise or containing backgound activity of adjacent epileptic spikes.

5) Topographic test: As a final step the information of different channels is integrated. A detection is approved if evolving repetitive waves were found on at least two neighboring channels, or on a single channel with sufficiently different signal pattern compared to all the other channels. Such patterns are combined into one seizure candidate segment. The latter property is computed with a global channelwise symmetry index, a measure similar to CSI, but where the spectral power of the actual channel is compared to all the other channels of the EEG:

$$GCSI_{ch,F} = \sum_{CH \neq ch} \sum_{f=F_{min}}^{F_{max}} \frac{PSD_{f,ch} - PSD_{f,CH}}{PSD_{f,ch} + PSD_{f,CH}} \quad (4)$$

After combining channel information the duration of the pattern selected as seizure candidate should exceed a certain threshold length for final approval.

C. Correction for artifacts

Observing the EEG datasets, four types of artifacts were identified which were contaminating the measurements: muscle artifacts, repetitive eye movements, alpha activity and chewing artifacts.

1) Muscle artifact removal: On one hand, muscle artifact can cause missed or late detections, when superimposed on ictal activity. On the other hand, low pass filtering of muscle activity can result in a regular pattern in beta band, which can be mistaken for an ictal pattern. Muscle artifacts were removed by a technique based on canonical correlation analysis (BSS-CCA) as introduced in [7]. The multichannel EEG signal is decomposed to mutually uncorrelated sources with different autocorrelation structures, and ordered by their autocorrelation coefficients. Muscle activity, having broad frequency spectrum, is expected to appear on the sources with lower autocorrelation. Components containing muscle activity pattern are selected by comparing the energy exerted by 3-15 Hz frequency band, containing real brain activity and by 25-50Hz frequency band, affected mostly by muscle activity:

$$EnergyRate = \frac{E(3-15Hz)}{E(25-50Hz)} \quad (5)$$

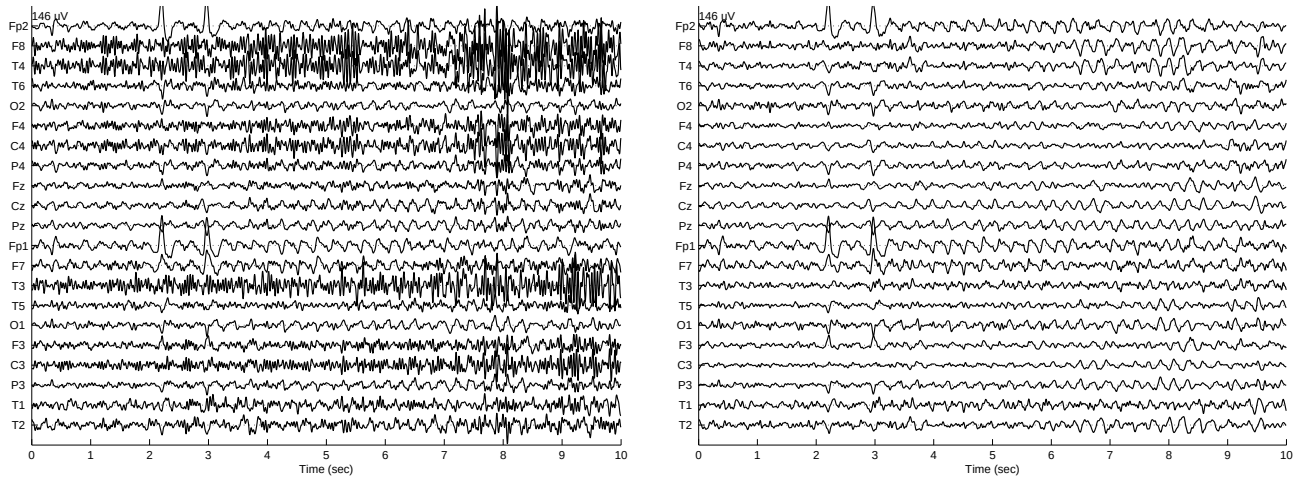

Fig. 1. Ictal EEG of a patient with temporal lobe epilepsy. Muscle artifacts are contaminating temporal and fronto-central channels, making both visual and automatic detection difficult. BSS-CCA succeeds in removing muscle artifact and revealing the hidden rhythmic pattern

The first component with an energy rate smaller than a certain threshold (set to 1.5 in this work) is excluded, together with all other components with lower autocorrelation. The clean signal is reconstructed by the remaining source signals. Fig. 1 illustrates how BSS-CCA succeeds in removing muscle artifact from an EEG segment with ictal activity.

2) Eye artifacts: On average referenced montage the eye artifacts can be projected on multiple channels. Therefore repetitive eye blinks can be mistaken for a seizure pattern. Correction for these artifacts was included in the wave extraction step. A spike was considered to be an eye artifact and was automatically rejected, if its amplitude was higher than 80 uV and appeared either on channel Fp1 or Fp2; or it appeared on a different channel but simultaneously with an eye artifact, and its waveform showed a high correlation with it.

3) Alpha activity: Alpha activity is a rhythmic 8-13Hz pattern on the occipital channels, occurring when the patient is in a relaxed, awake state. It can be misleading because of its regular pattern. It is unlikely to occur simultaneously with a seizure, therefore segments with strong alpha band activity centered occipitally can be simply discarded.

4) Chewing artifact: While eating, the movements of the tongue, the skin, and the chewing muscles create semi-rhythmic artifact on the EEG data. The pattern of this artifact is characterized by high voltage spikes occurring regularly after each other, superimposed by muscle artifacts. Due to the high voltage, the patterns occurring on different channels are closely correlated. Such segments with highly correlated signal pattern should be discarded.

D. Evaluation criteria

The performance of the seizure detection algorithm is evaluated in terms of sensitivity, false detection rate and alarm delay, defined as follows:

sensitivity: percentage of the detected seizures compared to the total number of recorded seizures

false detection rate: number of false detections divided by the total time of the measurement

alarm delay: time elapsed between the seizure onset according to the labeling and the moment the detection system is setting off the alarm

III. RESULTS

There is a trade-off between sensitivity and false detection rate. The performance of the algorithm can be easily tuned in favor of one or the other by adjusting the threshold length. Increasing threshold length will exclude false detections with short patterns resembling ictal periods, although, it will also cause missing true seizures which *a.* are too short *b.* are partially superimposed with artifacts or *c.* which the algorithm fails to recognize in their entire course. In this work the threshold length varied between 5s and 10s.

Table I shows the performance of the algorithm with and without applying BSS-CCA for muscle artifact removal, yet, without the final step of topographic test. The sensitivity increases significantly after muscle artifact removal, by an average of 9.85%, depending on the threshold length.

On the other hand, the number of false detections increases as well. This can be explained by the fact that removing the least autocorrelated CCA sources, the autocorrelated, thus seizure-like oscillatory components become more pronounced on the data. These non-seizure segments are usually detected on non-consistent or single channels, therefore, the topographic test efficiently excludes them. The final results are shown in Table II. Due to applying the final topographic test, one extra seizure was missed. However, decreasing the threshold length from 8s to 7s a higher sensitivity (84.4%) can be obtained, still preserving a comparable false detection

TABLE I
MUSCLE ARTIFACT REMOVAL

BEFORE

threshold length (s)	5	6	7	8	9	10
sensitivity (%)	81.3	78.1	71.9	71.9	71.9	68.8
false detection rate (/h)	2.13	0.90	0.48	0.30	0.24	0.17

AFTER

threshold length (s)	5	6	7	8	9	10
sensitivity (%)	90.6	90.6	87.5	78.1	78.1	78.1
false detection rate (/h)	1.77	0.90	0.53	0.36	0.26	0.23

TABLE II
AFTER TOPOGRAPHIC TEST

threshold length (s)	5	6	7	8	9	10
sensitivity (%)	87.5	87.5	84.4	75.0	75.0	75.0
false detection rate (/h)	0.62	0.40	0.24	0.20	0.18	0.15
alarm delay (s)	14	15	16	18	19	19

rate (0.24/h). The remaining false detections are mainly due to interictal epileptiform activity, or rhythmic, low-frequency activity of sleeping and drowsiness. Our method has an inherent lag between seizure onset and alarm set-off because of the 5s long epoch segments analyzed at once, and because of the threshold length set. Thus, a lower threshold length is also beneficial for a shorter alarm delay.



Fig. 2. Example of a successfully detected seizure. The black line depicts the seizure onset time according the to labeling, the red dotted line indicates the onset time found by the algorithm and the full red line corresponds to the alarm time. The highlighted signal segments correspond to the wave sequence identified by the algorithm as seizure activity.

IV. CONCLUSION

The seizure detection algorithm introduced here successfully detected epileptic seizures with a relatively low false detection rate. Low number of false detection is particularly important if used as a seizure onset alarm system in clinical environment. Nevertheless, the performance in terms of sensitivity and specificity can easily be tuned in order to meet the requirements of the current objective. The criteria used at most steps of the algorithm are data-driven, adaptively handling inter-patient variability of ictal patterns. However, there are parameters (the combined threshold T in step *2.* and spike template in step *4.*), which are not yet derived in a patient-independent way at the current stage of the algorithm. Alternative solutions for defining these parameters could offer further improvement in the detection performance.

ACKNOWLEDGMENT

This research is supported by the Research Council KUL: GOA MaNet, CoE EF/05/006 Optimization in Engineering (OPTEC), IDO 05/010 EEG-fMRI; the Flemish Government: FWO: G.0427.10N (Integrated EEG-fMRI) and IWT: TBM080658-MRI (EEG-fMRI); the Belgian Federal Science Policy Office: IUAP P6/04 (DYSCO, 'Dynamical systems, control and optimization', 2007-2011); and EU: Neuromath (COST-BM0601).

REFERENCES

[1] H.M. de Boer et al. ,The global burden and stigma of epilepsy *Epilepsy & Behaviour* Vol. 12, 2008, pp 540-546.
[2] J. Engel, Surgery for seizures *New England Journal of Medicine* Vol. 334(10), 1996, pp 647652.
[3] J.M.Stern, J.Engel, Ed., Atlas of EEG patterns, Philadelphia: Lippincott Williams & Wilkins, 2005.
[4] M.J. van Putten et al., A brain symmetry index (BSI) for online EEG monitoring in carotid endarterectomy, *Clin. Neurophysiol.*, vol. 115(5), 2004, pp 1189-1194.
[5] R.V.A.Sheoraypandaj et al., Reproducibility and clinical relevance of quantitative EEG parameter in cerebral ischemia: a basic approach H. Kwakernaak and R. Sivan, *Clin. Neurophysiol.*, vol. 120, 2009, 845-588.
[6] J. Gotman, Automatic recognition od epileptic seizures in the EEG, *Electoenceph. Clin. Neurophysiol.*, vol. 54, 1982, pp 530-540.
[7] W.De Clercq et al., Canonical correlation analysis applied to remove muscle artifact from the electroencephalogram, *IEEE trans. Biomed. Eng*, vol. 53(12), 2006, pp. 2583-2587.