34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Combining Time Series and Frequency Domain Analysis for a Automatic Seizure Detection

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Abstract— **The detection of epileptic seizures in long-term electroencephalographic (EEG) recordings is a time-consuming and tedious task requiring specially trained medical experts. The EpiScan [1–4] seizure detection algorithm developed by the Austrian Institute of Technology (AIT) has proven to achieve high detection performance with a robust false alarm rate in the clinical setting. This paper introduces a novel time domain method for detection of epileptic seizure patterns with focus on irregular and distorted rhythmic activity. The method scans the EEG for sequences of similar epileptiform discharges and uses a combination of duration and similarity measure to decide for a seizure. The resulting method was tested on an EEG database with 275 patients including over 22000h of unselected and uncut EEG recording and 623 seizures. Used in combination with the EpiScan algorithm we increased the overall sensitivity from 70% to 73% while reducing the false alarm rate from 0.33 to 0.30 alarms per hour.**

I. Introduction

ELECTROENCEPHALOGRAPHY (EEG) is the medical standard for examination of patients suffering from epilepsy. Long-term EEG recordings lasting for several days are needed for pre-surgical evaluation of patients with refractory epilepsy types or patients having inacceptable medical side-effects. The unpleasant situation for patients monitored continuously with video and EEG is impaired with an increased risk of seizures as anti epileptic drugs are reduced. Not only is a thorough analysis of the long-term EEG involving medical experts required but also a 24 hour surveillance of the EEG in real-time. An automatic method that marks seizure events can reduce evaluation time drastically and increases patient security by alerting medical staff immediately.

A major problem in the automatic seizures detection is the inter-patient variability of ictal patterns ranging from quasi periodic patterns over patterns with high frequency variation or abrupt phase changes to completely irregular groups of ictal discharges. The existing EpiScan algorithm [1–5] identifies ictal activity with rhythmic or periodic morphology using a continuous wavelet transform approach. This method has reached a high overall sensitivity and a low false alarm rate in uncut, unselected clinical data [4]. Ictal patterns with high frequency variation and phase changes were partly recognized by the EpiScan algorithm, but lead to higher overall false alarm rates.

In this paper a time domain algorithm for detection of epileptic seizures called *Epileptiform Wave Sequence* (EWS) analysis will be presented that is designed to reliably detect epileptic seizures with rhythmic morphology and especially addresses the group of ictal patterns with a moderate irregular structure, abrupt phase changes or distortions. In this context an epileptiform wave is a pathologic discharge seen in the EEG and a sequence is an epoch dominated by waves with the same properties.

Such wave sequences result from repeating discharges of groups of cortical neurons with abnormal hypersychronous behavior [6]. The post-synaptic electrical potentials [6] coming from a synchronous firing neuronal group in the seizure onset zone mix non-linearly with other physiological signals, will be attenuated at the skull bone and finally sum up with artifacts from scalp muscles and technical electrode artifacts. Ictal patterns with moderate irregular morphology are often seen in patients with ictal slowing, rhythmic delta activity or in a secondary generalization phase of the seizure when the rhythmic pattern at onset (PAO) was obscured. Figure 1 shows an example of an ictal signal interfered with noise that can be easily analyzed by a method based on a

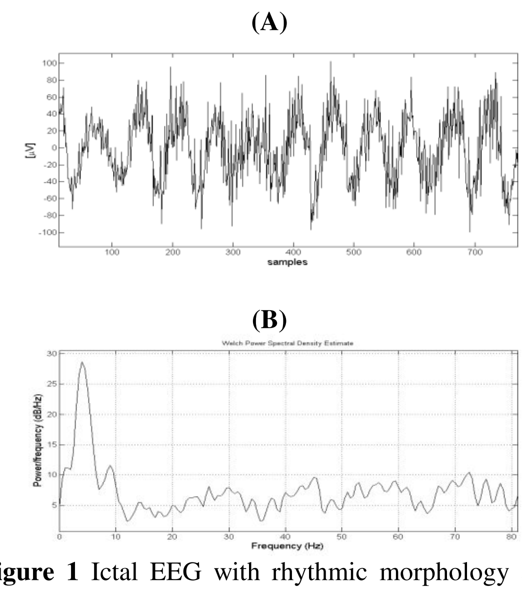

Figure 1 Ictal EEG with rhythmic morphology and with muscle artifacts **(A)** compared to the power spectrum of the same signal **(B)**. A method based on spectral analysis will be capable of detecting the underlying rhythmic pattern as the power spectrum reveals a strong peak at 4 Hz.

This work was supported in part by Grant WST3-T-81/014-2008 from the Provincial Government of Niederösterreich with the European Regional Development Fund, and by FWF Grant L585-B19.

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978-1-4577-1787-1/12/$26.00 ©2012 IEEE

spectral estimation. A time series analysis is preferable for the signal in Figure 2 because the more irregular distance between adjacent peaks do not result in a stable frequency for spectral estimation. Hence a combination of both approaches will be preferable.

Time-series algorithms that search for unique markers in the signal to segment and analyze the patterns are commonly used in the field of EEG analysis. Gotman e.g. [7–9] showed

(A)

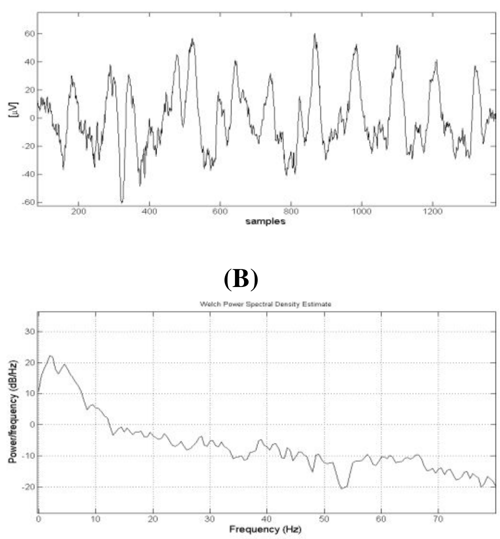

Figure 2 : Ictal EEG signal with an irregular morphology **(A)** that leads to a fuzzy spectrum after transformation in the frequency domain **(B)**. The power spectrum looks smeared and has equally high components from 2 to 5 Hz. The averaging of the spectral analysis obscures the simple structure of repeating discharges seen in the time series.

several applications with this approach. In this paper the method is evaluated using a comprehensive EEG database with statistical relevance.

II. METHODS

A. *Frequency domain analysis*

EpiScan utilizes a continuous wavelet transformation algorithm called *Periodic Waveform Analysis* (PWA) to search for rhythmic patterns in the surface electrode EEG channels. More details can be found in [2], and a complete performance analysis using the AIT EEG database can be found in [3].

B. *Time domain analysis*

The *Epileptiform Wave Sequence* (EWS) analysis was designed to reliably detect epileptic seizure patterns with rhythmic morphology in the time domain and especially encounter the problems of high frequency variation, abrupt phase changes and signal distortions by muscle or electrode artifacts. The EWS analysis will proceed as follows:

1. wave classification
2. wave clustering
3. sequence creation
4. intra-sequence correlation

Step 1 will find interesting signals called waves, Step 2 group waves with the same properties using a clustering algorithm. Step 3 then creates a sequence from waves belonging to the same cluster. Step 4 calculates a correlation value acting as similarity measure for the sequence.

1) Wave classification

To find epileptogenic waves, the signal is scanned iteratively over time for maxima of ictal discharges. A wave is defined as the signal between two adjacent maxima that fulfills the following classification criteria:

- the instantaneous frequency f_n has to be in range
- the dynamic d_n of the wave has to be high enough
- the high frequency noise of a wave has to be small

The instantaneous frequency f_n of wave n is the ratio of the sampling frequency f_s to the duration of the wave measured between time points of two maximum peaks τ_k^{max}.

$$f_n = \frac{f_s}{\tau_{n+1}^{max} - \tau_n^{max}} \qquad (1)$$

The dynamic of a wave d_n is measured using the two maximum values and the including minimum value t_{min_k}

$$d_n = \left|k(\tau_n^{min} - \tau_n^{max}) + x(\tau_n^{max}) - x(\tau_{n+1}^{min})\right| \qquad (2)$$

with the slope k defined as

$$k = \frac{x(\tau_n^{max}) - x(\tau_{n+1}^{max})}{\tau_{n+1}^{max} - \tau_n^{max}}. \qquad (3)$$

The high frequency noise of a wave is measured using the sum of squares of all adjacent signal points $x(t)$ in the wave. This wave-extraction scheme will solve the problems of phase changes, signal distortion and high frequency variation as all waves are handled separately. Only a sequence of epileptogenic waves with similar morphology reliably specify a seizure pattern, so a sequence needs to be found.

2) Wave clustering

Waves will be clustered using the measures found in the wave classification step. The clustering algorithm uses a given variance to find a single subgroup that dominates the ictal EEG. The variances were found using a statistical analysis of the AIT EEG-database and cross-validation with knowledge from specially trained EEG experts. Clustering is done sequentially using the instantaneous frequency, wave amplitude and the noise measure.

3) Sequence creation

After wave clustering a sequence will be defined allowing gaps that correspond to signal distortions. This step will create the sequence using only clustered waves but leaving out signal epochs with artifacts. This will avoid mixing artifacts and interesting signals like in the spectral widening problem of the FFT [10]. An example of an ictal EEG in the delta band with marked waves as sequence is shown in Figure 3.

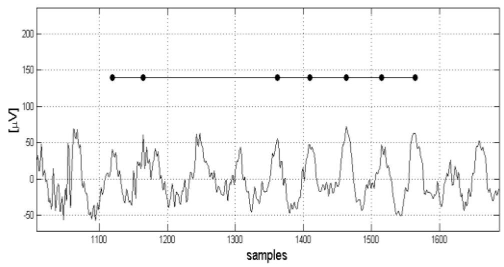

Figure 3 Ictal EEG (sampling frequency 256 Hz) with a repeating but irregular morphology and the detected sequence marked with filled circles at the end of the wave. Note that some waves are left out as they do not fit into the cluster or the sequence restrictions.

4) Intra-sequence correlation

The morphology of the waves in the sequence is used to separate artifacts from ictal patterns based on the observation that ictal sequences of epileptogenic discharges look similar to each other. A similarity value γ is calculated that models the similarity in a group of waves. Note that the morphology is not pre-defined but only must be similar in the sequence. This will avoid correlation artifacts as in cosine or wavelet transforms where a signal needs to be decomposable into the respective signal forms. The similarity value γ is calculated using the signal of N extracted waves $w_n(t)$.

$$\gamma = \left. \frac{var_\tau\left(E_n\left[w_n(\tau)\right]\right)}{E_n\left[var_\tau\left(w_n(\tau)\right)\right]} \right| n \in 1..N, \tau \in \tau_n^{max}..\tau_{n+1}^{max} \tag{4}$$

The measure γ will then be used as replacement for the PWI feature in the EpiScan algorithm as described in [2].

C. Performance analysis

1) *Sensitivity:* The detection sensitivity was evaluated as follows: Each marker of electrographically visible seizures that intersects with a seizure alert from the algorithm is regarded as true positive event, whereas each seizure marker with no intersection is a false negative event. For each patient with recorded seizures the sensitivity is determined as the ratio of true positives and the total number of recorded seizures. We evaluate these sensitivities by calculating the mean over all patients with seizures. Averaging over patient-wise sensitivities is done since seizure counts of the patients are not equally distributed.

2) *False alarm rate:* The false alarm rate is also calculated patient-wise. Long contiguous markers from an automatic seizure detector create a higher review effort than short ones that can be inspected on a single EEG screen. In order to accommodate this fact, each seizure alert is divided into multiple sub-markers of maximally 30 seconds, meaning that each of these markers contributes to the false alarm rate. Each sub-alert that does not intersect with a true seizure marker (basic truth) is regarded as a false alarm. The number of false alarms for one patient divided by the total number of hours of EEG recordings for this patient gives the false alarm rate. False alarm rates are evaluated by calculating the mean over all patients.

D. Test set

The EEG database of the AIT [1] was used to validate the seizure detection performance. The database includes solely uncut and unselected EEG long-term recordings from several epilepsy monitoring units, mostly in 256 Hz sampling rate using the standard 10-10 or 10-20 international electrode system.

AIT EEG Database	Measure
# Patients	275
# Patients with epilepsy	159
# Patients with seizures	96
# Epileptic seizures	623
# Hours of EEG recordings	22463

Table 1 Overview of the AIT EEG database

III. Results

A. EWS Detection Performance

The EWS algorithm reached 100% detection sensitivity in a third of the patients (N=31). The mean of the detection sensitivity using all patients with all epilepsy types (N=96) is 53%. The overall false alarm rate of all patients (N=275) was 0.14 false alarms per hour (FA/h).

B. Combined EpiScan and EWS Detection Performance

To optimize the detection performance without further increasing the false alarm rate (compared to [4]) a PWA setting with reduced sensitivity was combined with the EWS algorithm. Figure 4 draws the detection sensitivity as function of the false alarm rate showing that the combination with the EWS algorithm is preferable to a further increase of the PWA sensitivity. The advantage of the combined version is an increase of 3% in sensitivity and a reduction of 0.034 false alarms per hour (FA/h) giving absolute values of 73% overall sensitivity (N=96) with an overall false alarms rate (N=275) of 0.3 FA/h. The combination leads to an improvement because irregular ictal patterns are detected more efficiently with the EWS algorithm.

A histogram showing the detection performance of the combined method is given in Figure 5. Note that the majority of patients (N=52) had a detection sensitivity of 100%. The important subgroup of temporal lobe epilepsy (TLE) patients (N=61) is detected with high sensitivity of 83.6% and a false alarm rate of 0.29 FA/h.

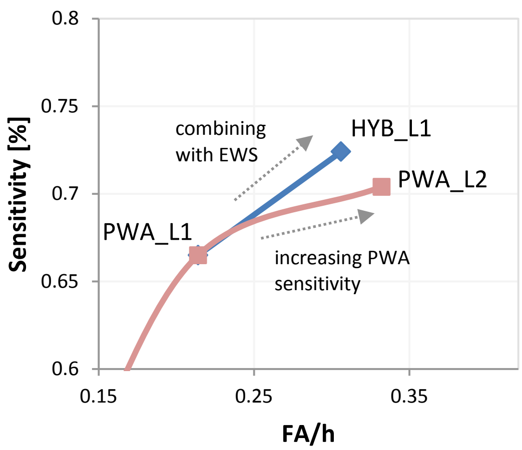

Figure 4 The plot of the algorithm operating characteristic (AOC) shows the overall detection sensitivity in percent against the false alarm rate per hour (FA/h)**.** The marker PWA_L2 correspond to EpiScan algorithm solely based on PWA published in [4]. The EWS algorithm is combined with the setting PWA_L1 to raise sensitivity while reducing FA/h compared to PWA_L2, giving the marker HYB_L1.

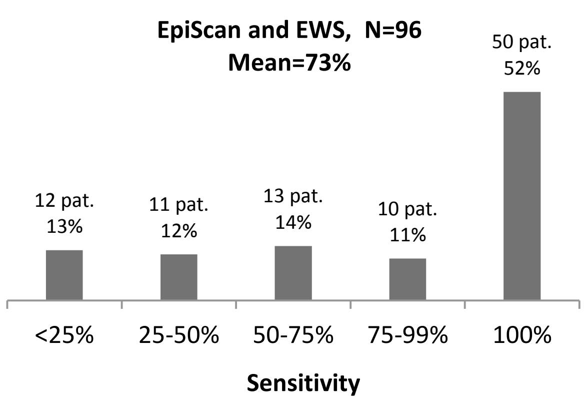

Figure 5 The histogram of the combined detection performance using the PWA_L1 and the EWS algorithm. Most of the 96 patients with seizures have a detection performance of 100%, patients having lower detection sensitivities are nearly equally distributed. The mean of the detection sensitivity is 73%.

IV. Discussion

A time domain approach of an epileptic seizure detector called EWS was presented that showed its effectiveness in detection of rhythmic seizure patterns with moderate irregular morphology or signal distortions. The combination with the EpiScan algorithm leads to a new hybrid detection scheme with a performance that could not be reached by one algorithm alone. An overall detection sensitivity of 73% while having a false alarm rate of 0.3 was reached that correspond to an increase of 3% in sensitivity and a reduction of 0.034 in false alarm rate compared to [4]. The performance of the important group of TLE patients reached a sensitivity of 83.6% with a false alarms rate of 0.29 alarms per hour.

The analysis of the problems and results imply that many feature extraction schemes working on biomedical signals face similar problems and that they will benefit from hybrid algorithm approaches as the strengths of both viewpoints are needed to bring performance to new levels.

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