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EpiScan: Online seizure detection for epilepsy monitoring units

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Abstract—**An online seizure detection algorithm for long-term EEG monitoring is presented, which is based on a periodic waveform analysis detecting rhythmic EEG patterns and an adaptation module automatically adjusting the algorithm to patient-specific EEG properties. The algorithm was evaluated using 4.300 hours of unselected EEG recordings from 48 patients with temporal lobe epilepsy. For 66% of the patients the algorithm detected 100% of the seizures. A mean sensitivity of 83% was achieved. An average of 7.2 false alarms within 24 hours for unselected EEG makes the algorithm attractive for epilepsy monitoring units.**

I. Introduction

APPROXIMATELY one percent of the world's population suffers from epilepsy, a chronic dysfunction of the brain that is characterized by recurrent unprovoked and unpredictable seizures caused by an excessive discharge of groups of neurons. While 65% of epilepsy patients can become seizure free using antiepileptic drugs, the remaining 35% suffer from medically refractory epilepsy. Epilepsy surgery represents a valuable treatment option for some of these patients. Successful epilepsy surgery critically depends on a thorough presurgical evaluation. Long-term electroencephalogram (EEG) recordings over several days are the corner stone for the presurgical workup for these patients. These recordings and their analysis are extremely time consuming and expensive. An automatic online seizure detection system would therefore be of great benefit. It would alert medical staff to a beginning seizure so that they can set appropriate medical actions improving patient safety and perform further systematic neurological testing during the seizure without continuously monitoring the EEG during the whole recording period. For offline analysis of long-term EEG recordings an efficient seizure detector could significantly reduce the data review effort. Furthermore, reliable automatic detection of epileptic seizures is a key technology for closed-loop intervention systems that could interrupt seizures with electrical stimulation, drug infusion, cooling, or biofeedback [1-3].

The EpiScan seizure detector presented in this paper was developed as an alerting device for epilepsy monitoring units (EMU). Such an online-detection system must recognize an occurring seizure through an analysis of the recorded EEG in real-time and with least possible latency. This requires an analysis of the EEG as a continuous data stream, where each new data sample is processed as soon as possible and alerting decisions are made upon samples from the past only. The inputs to the algorithm are EEG recordings only. The electrodes from the ten-twenty electrode system [4] are required as minimum channel set. Additional channels might improve the performance. The seizure detector has to produce seizure alerts or markers with the following four major requirements:

1) *High sensitivity:* The algorithm must find as many seizures as possible. Each missed seizure might bear potentially dangerous situations for the patient and reduces the chances for significant clinical findings.

2) *Low latency:* In order to enable neuropsychological tests during a seizure without continuously monitoring the EEG, the epileptic activity must be detected with least possible latency. It should be noted that, in contrast to seizure prediction, in seizure detection the goal is to create markers or alerts shortly after the first signs of a seizure become visible in the EEG.

3) *High specificity:* The algorithm must produce as few false alarms as possible. This requirement is of great importance for the acceptance of an alerting device in clinical practice. A system producing too many false alerts might be ignored or even switched off.

4) *Easy-to-use:* For usability in clinical practice an automatic seizure detector must be parameter-free. It should not be required to adjust patient-specific parameters in order to achieve satisfying detection performances.

For the development of a seizure detector numerous challenges must be met. First of all, a sufficiently large data set of annotated EEGs which have been recorded in an EMU must be available. For a fair performance evaluation, annotations must be made from the EEG only, i.e., without videos showing clinical signs, which are not observable for the EEG-based detection algorithm.

A major reason why seizure detection is still a challenging problem is the high inter-patient variability of the EEG. Patients have various ages, epilepsy syndromes and even multiple additional diseases. Algorithms have to adapt to the properties of each patient's EEG since patient-specific parameters cannot be adjusted manually.

Large scale temporal changes in the characteristics of EEGs lead to further challenges. E.g., varying EEG characteristics due to sleep-/wake-stages or variations of signal quality due

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to changing electrode-tissue-impedances cause problems that can be faced by means of adaptation methods.

After all, strong signal artifacts are inevitable if recordings last for several days. All kinds of artifacts must be considered, but movement artifacts, chewing artifacts, eyelid fluttering artifacts might cause the most problems in an automatic seizure detection system.

Seizure detection has a long history of scientific publications. Moreover, it is already available in commercial software packages. However, to our knowledge the acceptance of these packages in epilepsy centers is poor. One major reason for this might be that false alarm rates are still too high for everyday use, when EEGs are unselected.

One of the most prominent attempts to seizure detection was made by Gotman [5], based on a decomposition of the EEG into elementary waves and the detection of paroxysmal bursts of rhythmic activity. Gotman published another, Bayesian approach in [6]. EEG recording systems e.g. from Stellate Systems, Inc. and from NIHON KOHDEN are available with a seizure detection algorithm from Gotman.

The performance of another algorithm called "Reveal" was analyzed in[7]. This algorithm is based on Matching Pursuit and designed to identify particularly rhythmic components. The Reveal algorithm is commercially available e.g. in NIHON KOHDEN devices and in the EEG software packages from Persyst Development Corp.

Recently Optima Neuroscience, Inc. offered another seizure detector called IdentEvent [8]. It is based on pattern-match regularity statistic (PMRS), local maximum frequency (LMF), and amplitude variation (AV).

Promising detection performance was also achieved in an algorithm presented in [9], where seven EEG signal features are used as inputs of a support vector machine.

In this paper, we present a seizure detection algorithm based on the Periodic Waveform Analysis [10] with a novel baseline adaptation module. This algorithm has been implemented in C++ and is about to be introduced as an online alerting system in a clinical environment in 2011. Here we present the results from an off-line analysis of the detection performance, whereby online processing was simulated.

II. Materials and Methods

A. Algorithm

The EpiScan algorithm consists of six building blocks, which are illustrated in Fig. 1.

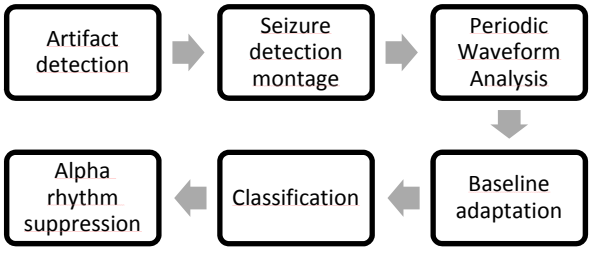

Fig. 1: Block diagram of the EpiScan seizure detection algorithm.

The EEG signals are sequentially processed by the modules "Artifact detection", "Seizure detection montage", "Periodic Waveform Analysis", "Baseline adaptation", "Classification", and "Alpha rhythm suppression", which will be described in the following:

1) *Artifact detection:* The first module detects and marks epochs of impaired signal quality, mainly caused by technical problems like dry electrodes, strong interferences from external electrical devices, saturating amplifiers or analog-to-digital converters, or strong movement artifacts. This artifact detection is based on simple signal features like EEG amplitudes, EEG variances, and singularities of power spectral densities.

2) Seizure detection montage: In the visual EEG analysis three montages are commonly used: referential montages, longitudinal montages and transversal montages. We created a special seizure detection montage that includes all referential channels, and a selection of the most important bipolar channels out of the transversal and longitudinal montages. This selection was chosen manually, but is kept constant for all patients.

3) Periodic Waveform Analysis: The core of the EpiScan seizure detection algorithm is an algorithm called periodic waveform analysis (PWA), which was designed to detect rhythmic EEG patterns *[10]*. For temporal lobe epilepsies, these are the most frequent patterns. The PWA starts with a calculation of the total harmonic energy E_τ of an EEG signal x_t via

$$E_\tau = \sum_{m>0} \left| \frac{1}{\sqrt{\tau}} \int_{-\infty}^{\infty} x_t \, \psi^*_{t/\tau} e^{-j2\pi \frac{mt}{\tau}} dt \right|^2, \qquad (1)$$

which is calculated for cycle durations τ within a range

$$\tau_{min} \le \tau \le \tau_{max}.$$

The rectangular time window ψ_t selects x_t within an interval centered about $t = 0$ and must be chosen such that the energy is bounded. A maximization of E_τ in (1) yields the dominant cycle duration $\hat{\tau}$ and subsequently the Periodic Energy Index (PEI) defined as

$$\mathrm{PEI} = E_{\hat{\tau}}. \qquad (2)$$

The signal energy corresponding to a cycle-duration τ is defined as

$$N_\tau = \frac{1}{\sqrt{\tau}} \int_{-\infty}^{\infty} \left| x_t \psi^*_{t/\tau} \right|^2 dt.$$

Finally the periodic waveform index (PWI) is defined as

$$\mathrm{PWI} = \frac{E_{\hat{\tau}}}{N_{\hat{\tau}}}. \qquad (3)$$

This is the ratio of E_τ in (1) and N_τ in (3) evaluated at dominant cycle-duration $\hat{\tau}$. The PWI is unity for perfectly rhythmic (periodic) signals and approaches zero for totally non-rhythmic signals.

4) *Baseline adaptation:* The time-varying dynamics of epileptic seizures and the high inter-patient variability make their detection difficult. Similar to the approach presented in *[11]* PWI values are split into three frequency bands PWI_δ, PWI_θ, and PWI_α. Then the P-th percentiles $T^P_\delta(t,d)$, $T^P_\theta(t,d)$, and $T^P_\alpha(t,d)$ of the separated PWI values within a time window ranging from $t-d$ to t are calculated and used

to normalize the PWI values. The window range d should be chosen in the order of two to four hours.

5) *Classification:* In this module a classification of the normalized values of PWI_δ, PWI_θ, PWI_α, PEI_δ, PEI_θ, and PEI_α leads to seizure alerts. This classifier is designed such that PWI values must be above fixed thresholds and PEI values must be within certain ranges defined for each band separately. Contiguous alerts with a distance of less than 30 seconds are merged into single seizure alerts, since it is assumed that they do belong to the same seizure.

6) *Alpha-rhythm suppression:* When seizures are detected based on rhythmic patterns, alpha rhythms can be a significant source of false alarms. In order to reduce these false detections to an acceptable level, the maximum amplitude of each pattern in the alpha band is localized by means of the PEI in (2). This information can be used to suppress occipital and parietal alpha rhythms.

B. EEG data and basic truth

The EpiScan seizure detection algorithm was tested with EEG recordings from 48 patients with temporal lobe epilepsy (TLE). The recordings from 38 patients included seizures, for 10 patients no seizures could be recorded. The complete data contain 4.300 hours of EEG including 224 seizure annotations. All recordings where retrieved from an epilepsy monitoring unit and taken "as they are", i.e., data were not selected according to their signal quality.

In order to analyze the performance of a seizure detection algorithm, annotations of seizures that are visible in the EEG are required. However, the original annotations in the EEGs additionally contain markers of seizures that have been reported by patients only, or those which could be recognized via clinical signs in the video recordings. Thus we created a list of annotations of seizures that could be recognized in the EEG, without watching the videos and using the following procedure:

Two EEG technicians were asked to re-evaluate the EEG recordings of a set of "potential seizure markers" including the following positions:

1) All original seizure markers from the clinical reports, which were obtained from the video-EEG.
2) A set of "false alarms" of a previous version of the presented seizure detector. Hereby we chose the false alarms featuring the highest PWI values, i.e., the most rhythmic patterns that have not been marked as a seizure in the clinical report.
3) A randomly chosen set of arbitrary markers.

These sets were chosen such that 50% of the positions were original seizure markers, 35% featured high PWI values, and 15% were chosen randomly.

The EEG technicians reviewed these EEG positions without access to clinical reports and without video recordings. They were asked to rate each potential marker with the following categories:

1) Certainly a seizure (>90%)
2) Probably a seizure (>75%)
3) Rather a seizure (>50%)
4) Rather not a seizure (<50%)
5) Probably not a seizure (<25%)
6) Certainly not a seizure (<10%)

We considered markers rated with either "Certainly a seizure (>90%)", "Probably a seizure (>75%)", or "Rather a seizure (>50%)" being electrographically visible EEG seizure markers for performance evaluation.

C. Performance analysis

1) *Sensitivity:* The detection sensitivity was evaluated as follows: Each marker of electrographically visible seizures (cf. Subsection II B) 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 means of histograms and 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, which 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 also evaluated by means of histograms and by calculating the mean over all patients (with seizures).

III. Results

From 224 original seizure annotations in the EEGs 186 were rated as electrographically visible seizure marker (cf. Subsection II.B). The remaining 38 annotations were rejected as electrographically invisible.

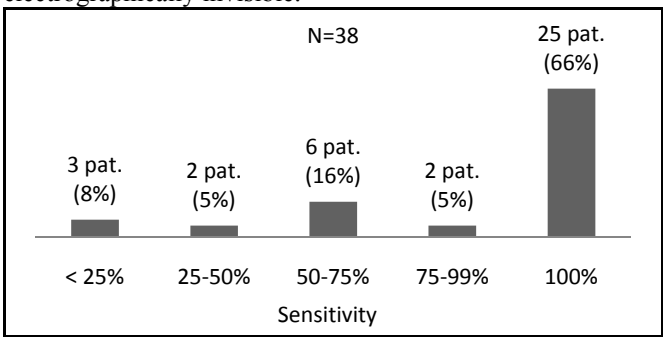

Fig. 2: Histogram of sensitivities. For 8% of the patients sensitivity was lower than 25%, for 5% sensitivity was between 25% and 50%, for 16% of the patients sensitivity was between 50% and 75%, for 5% it was between 75% and 99%, and for 66% of the patients it was 100% (all seizures detected).

The EpiScan was evaluated with the EEG recordings from patients with seizures as described above. We obtained a mean sensitivity of 83%, i.e., on average over all patients more than 4 out of 5 seizures were successfully detected. However, the distribution of patient-wise sensitivities is strongly non-symmetric. Thus a histogram is depicted in Fig. 2, yielding more precise information. For 66% of the patients with seizures (N=25) the algorithm detected actually all seizures and for only 13% of the patients (N=5) it showed sensitivities below 50%.

From our evaluation of patient-wise false alarm rates we obtained an average value of 0.30 FA/h for all data, including patients with no seizures (N = 48). Again, due to the strong non-symmetric distribution of these values we present the false alarm rates by means of a histogram in Fig. 3. Here it can be seen that for 40% of the patients (N=19) there was less than one false alarm every five hours, and for 65% of the patients (N = 31) there was less than one false alarm every 3 hours. For 85% of the patients (N=41) we had less than one false alarm every two hours and the remaining 15% of the patients (N=7) the false alarm rate was between 0.5 and 1 FA/h.

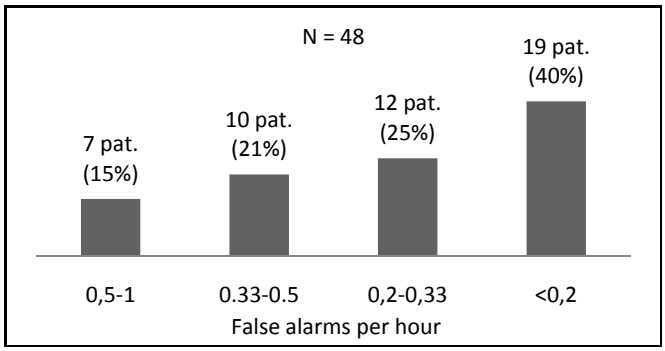

Fig. 3: Histogram of false alarm rates. For 40% of the patients the false alarm rate was below 0,2 FA/h, for 25% it was between 0,2 and 0,33 FA/h, and for 21% of the patients the false alarm rate was between 0,33 and 0,5 FA/h. Only 15% showed a false alarm rate between 0,5 and one FA/h.

IV. Discussion

In this paper EpiScan, an algorithm for seizure detection in epilepsy monitoring units, was presented and its performance was evaluated in terms of sensitivity and false alarm rate. The core of EpiScan is a periodic waveform analysis, an algorithm which detects rhythmic EEG patterns that can be found most frequently in epileptic seizures. A baseline normalization module performs adaptations to patient-specific EEG properties, leading to a completely parameter-free seizure detection system.

In the performance evaluation using EEGs from 48 TLE patients we achieved 100% sensitivity for 66% of the patients and a mean sensitivity of 83%. The mean false alarm rate was 0.3 FA/hour or 7.2 FA within 24 hours. These results were obtained with EEGs that had not been preselected, thus we believe that the EpiScan algorithm can provide a substantial benefit for epilepsy monitoring units.

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