

Automated Detection of Epileptic Seizures in the EEG

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Abstract—A system has been developed to detect epileptic seizures in real-time during long-term EEG (LTEEG) monitoring. LTEEG is an important clinical service provided by the Neurology Department at Christchurch Hospital to investigate patients who have relatively infrequent but recurring seizures over extended periods. The detection algorithm looks for extended amplitude and frequency changes, calculated using basic signal-processing techniques, followed by a rule-based stage which compares time-dependent features against dynamic thresholds for each channel. Spatial context is used to discriminate eye artifacts. The system was tested on EEG data from 5 patients containing 44 epileptic seizures. The sensitivity and selectivity of the algorithm were 88.7% and 92.6% respectively.

Keywords—Epilepsy, Long-term EEG, Seizure detection

I. INTRODUCTION

Epilepsy is one of the most common of the neurological disorders, with a prevalence of about 1% of the population or 50 million persons worldwide [1]. Long-term EEG (LTEEG) monitoring is used to closely monitor patients over extended periods who have relatively infrequent but recurring atypical ‘turns’ or seizures. LTEEG monitoring comprises continuous 19-channel EEG and video recordings over several days. This allows the seizures to be ‘captured’ for in-depth off-line analysis. This information enables the neurophysiologist/neurologist to determine whether or not such seizures are of epileptic origin and, if so, determine the type and location of the epileptogenic activity in the brain. Currently, the occurrence of a seizure can only be recorded by having the patient, a nurse, or a relative, push a seizure button which results in a pre-set period of EEG before and after the pressing of the seizure button being stored for viewing at

some later stage. If for any reason the seizure button is not pressed, the EEG relating to that seizure is lost. The ability to detect seizures automatically in the EEG will substantially reduce the loss of valuable data due to the manual seizure button not being pressed.

Unlike spike-and-waves, a seizure is not primarily an electrographic pattern of characteristic morphology, but rather a behavioral event [2, 3] (e.g., Fig. 1 and 2). This wide-ranging electrographic morphology and, in some cases, lack of clear EEG manifestations, can make some seizures very difficult to detect reliably.

The aim of this project was to develop a real-time signal-processing algorithm to detect epileptic bursts and seizures in the EEG. Several approaches have been developed elsewhere, with varying success, in attempts to automatically detect epileptiform activity and seizures in the EEG. In most of these, the tendency has been to look for extended amplitude and frequency changes rather than aiming to capture characteristic waveforms. Because of the widely varying morphology of seizures, we also chose to incorporate measures of extended amplitude and frequency changes, as central features in our multi-stage detection algorithm.

II. METHODOLOGY

Our seizure detector incorporates a sequence of steps, comparable with those in the manual process applied by the expert electroencephalographer (EEGer).

To keep the algorithm as versatile as possible, the algorithm is largely montage independent. However, for optimum performance, the montage is best kept constant throughout a recording.

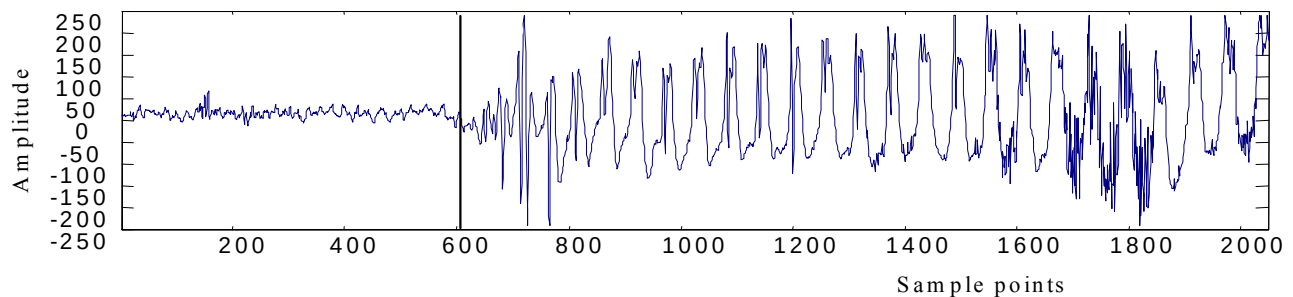


Fig. 1. Clear electrographic pattern of a seizure detected by the algorithm in one channel of EEG#1. Seizure starts at the vertical line.

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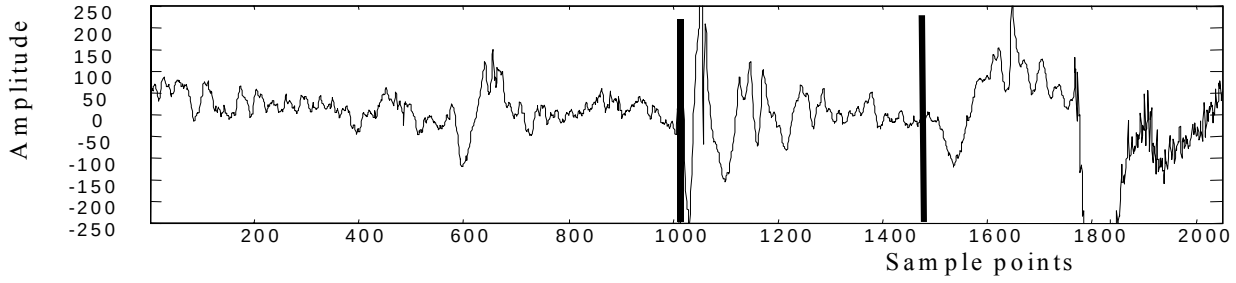


Fig. 2. Electrographic pattern of seizure detected by the algorithm in one channel of EEG#5. Seizure occurred between the vertical lines.

A. Calculation of features

Most seizures include some rhythmic discharge of high amplitude (low amplitude desynchronized EEG often marks their onset) and, at some time during their development, include paroxysmal rhythmic activity compared to the background, with frequencies varying from 3–20 Hz and relatively sustained in duration [2, 4, 5].

The algorithm calculates, the Average Dynamic Range (ADR) and the Frequency Vector (FV), representing amplitude and frequency features respectively, for every channel and over 256 sample epochs:

ADR – Each epoch is sub-divided into segments of 64 data-points, with overlaps of 32 data-points. In each segment the dynamic range (DR) (maximum - minimum) of the amplitude is calculated. The Average DR in an epoch is its ADR [6].

FV – Because the EEG data contains only one sample function and not the whole ensemble, assumptions about the ergodicity and statistical properties are estimated from time (rather than ensemble) averages [7]. The periodogram of an epoch is estimated from finite segments. This method is known as weighted overlapped segment averaging:

$$|X(f')|^2 = \frac{1}{I} \sum_{i=1}^I |X(f)|_i^2$$

$$\hat{S}(f) = \int W(f - f') |X(f')|^2 df'$$

The FV for each epoch is estimated from the power spectrum of each of its half-overlapping 64 point segments. Power spectra are calculated using a 64 point FFT. The mean of all 15 power spectra is convoluted with a Hanning window function resulting in a vector representing the frequency features of an epoch.

Temporal context information is used to make the algorithm insensitive to gain settings. The calculated features are stored in a moving window of 30 epochs representing the background of the EEG recording. The background is used to evaluate current epoch features against relative dynamic thresholds in the rule-based stage. To obtain a clear background, epochs containing high amplitude activity or large frequency changes, relative to the last 30 epochs, are rejected from the background.

B. Using prior knowledge

To determine if the calculated features of an epoch represent a seizure, the features are compared to the features of epochs containing definite seizures. The widely varying morphology of seizures makes it difficult to use static (absolute thresholds) comparison methods. Hence, relative dynamic thresholds are calculated: relative ADR (RADR) by dividing the ADR with the mean of the background, and the weighted distance function (DFV) between the FV of the current epoch and the mean of the background.

Single-channel rules in the rule-based stage are determined empirically and in a sequence. The first rule separates the candidate seizure epochs from the raw data by comparing the RADR and DFV with thresholds. To determine these thresholds, scatter plots of RADRs and DFVs from epochs containing confirmed seizure and non-seizures were generated for the 5 EEGs (e.g., Fig. 3).

The next rule discriminates seizures from large frequency changes in the common frequency bands (α and β). This is done by determining a direction coefficient (DC) from the FV of the current epoch. The final single-channel rule rejects muscle artifacts by determining the ratio of power in the high to the low frequency ranges.

Prior to the final decision, spatial context information is added in some multi-channel rules to reject eye-movement and eye-flutter artifacts. An epoch is rejected if events occur only on frontal channels. An epoch is also rejected if the candidate seizure occurs on less than 4 channels.

C. Test data

Sixteen channels of EEG were recorded via several bipolar and referential montages from scalp electrodes placed according to the International 10-20 system. The amplified EEG was band-pass filtered between 0.5–70 Hz, sampled at 200 Hz and digitized to 12 bits.

The performance of the system was tested on EEGs (2.15 h) containing epileptiform activity from five patients ranging 5–65 years.

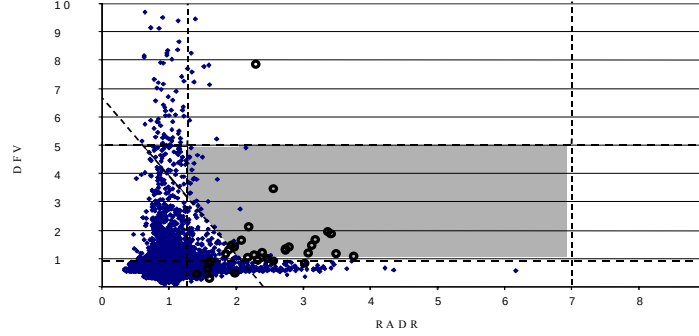


Fig. 3. Feature representation in EEG#4. $\circ$ represents a seizure epoch. $\bullet$ represents a non-seizure epoch. The plot shows difference in distribution between the non-seizure epochs and seizure epochs. Possible seizures are identified by having their ADR and FV features fall within the filled area

The data contained 71 *true seizure events* (TSEs), defined as epileptiform bursts of 1 s or longer and marked by at least 2 of the 3 EEGers as definite or by one as definite and 2 as questionable. This data set was considered by one of the EEGers (GC) to contain a sufficient number and variety of electrographic patterns to adequately test the algorithm.

D. Performance

Each EEG was presented to the seizure detector. Measures of sensitivity, selectivity and false detection rate were calculated for each EEG as

$$\text{Sensitivity} = \frac{\text{Total TP}s}{\text{Total TSEs}}$$

$$\text{Selectivity} = \frac{\text{Total TP}s}{\text{Total TP}s + \text{Total FP}s}$$

$$\text{False detection rate} = FPh = \frac{\text{Total FP}s}{\text{hour}}$$

Where TP is a true positive detection (correct detection of a TSE) and FP is a false positive detection. If epileptiform events were detected which were not TSEs (such as spikes and sharp waves), they were removed from the analysis.

III. RESULTS

From the single-channel feature representation in Fig. 3 it can be seen that the weighted distance of the FV and the ADR in relation to the background give, on their own, quite acceptable discrimination between seizures and other activity in the EEG.

Overall, the algorithm has a sensitivity of 88.7%, a selectivity of 92.6%, and an FPh of 2.3 (Table I).

IV. DISCUSSION

Most of the missed seizures occurred soon after a montage change, due to the relative dynamic thresholds not having settled. Ironically, a problem seen in EEG#2 was that too many seizures occurred over a relatively short period of time; this was due to the background used in the rule-based stage being inadequately estimated due to frequent rejection of epochs containing seizure activity. Because of the different montages in the recorded data, rejection of eye-blinks was not optimal and was the cause of about one third of the false detections in EEG#3. Another cause of the lower selectivity

rate, in EEG#3 was an unstable background due to frequent spikes.

Further improvements appear achievable in both the features and rule-based stages. A self-organising map in conjunction with fuzzy logic [6, 8] is a possibility for optimizing the rule-based stage. Wavelets [9] or non-linear complexity analysis [10] might also be used to calculate more discriminating features and, hence, improve both sensitivity and selectivity.

V. CONCLUSION

The idea of single-channel features to represent the EEG signal appears satisfactory for detection of epileptic bursts with a reasonable sensitivity and selectivity. Furthermore, the seizure detection algorithm has been translated from Matlab to C++ so as to operate in real-time.

The seizure detection system presented in this paper has only just been clinically commissioned in the LTEEG service of the Department of Neurology. As this system records all EEG data on a single (referential) montage, at least slight improvements in performance are likely to be obtained immediately. Either way, automated seizure detection should lead to substantial improvements in the LTEEG service by reducing the loss of valuable seizure data through the seizure button not being pressed and through the detection of sub-clinical seizures.

TABLE I
ALGORITHM'S PERFORMANCE

EEG	Age (years)	Events	Time (h:m:s)	Sens. (%)	Sel. (%)	FpH
EEG#1	17	2	0:25.41	100	100	0
EEG#2	46	51	0:26.15	92.2	100	0
EEG#3	65	8	0:23.24	50.0	44.4	12.8
EEG#4	12	9	0:26.18	100	100	0
EEG#5	5	1	0:27.24	100	100	0
TOTAL		71	2:09.02	88.7	92.6	2.3

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