Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Patient Un-Specific Detection of Epileptic Seizures Through Changes in Variance

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***Abstract*— Despite much progress and research, fully reliable computer based epileptic seizure detection in EEG recordings is still elusive. This paper outlines a new strategy toward seizure detection. It is proposed that it is not the precise nature of a statistic that is important, but rather its variance over time. Using this, algorithms are presented that are able to successfully identify 97.6% of seizures from over 170 hours of recording and 15 different patients. False positives remain high, but virtually no pre-processing has been applied to the raw data and it is expected that this can be improved with further work.**

I. INTRODUCTION

Much work has been dedicated to the prediction of epileptic seizures using electroencephalographic (EEG) recordings (see [6] for a review). However, due to the diversity of epileptic events even the simpler problem of reliably detecting seizures has not yet been solved. Seizure detection is important in clinical situations because EEG recordings are currently *visually* inspected to find and classify such events. The costs associated with this are significant, and the possibility of human error during this repetitive task is quite high. Automation of some if not the entire process would be invaluable.

The reason that reliable detection is difficult lies in the large variability in observables during epileptic events. For example: although many seizures involve large amplitude oscillations, there are others whose amplitude is no larger than previous activity; channels become synchronized during seizures, but not all channels are necessarily involved in an episode; seizure onset and offset are usually abrupt, but some are capable of appearing more slowly. This variation in observables occurs between patients, between seizures in the same patient, and *within* a single seizure. It is difficult for one single statistic, or a group of cleverly selected ones, to capture all possible combinations of symptoms reliably.

Many seizure detection strategies have been published in the past. Most work done in the 1980's and early 1990's produced results with 70-80% positive detection rate, and very high false positive rates [3], [4]. Furthermore in most work a particular type of epilepsy or phenomena was targetted. No global algorithm was proposed. More recently, very high success rates have been reported by some. Shoeb et al [1] use support vector machines (SVM) while Gotman et al [5],[7] use time-frequency analysis. Although successful, these techniques require patient-specific training and visual inspection by an expert is still necessary prior to classification in order to train the algorithm. Such methods are particularly suitable for ambulatory environments where patients have already been diagnosed.

Others have claimed high rates of success without the need for training by using non-linear analysis ideas. However, these methods are computationally very involved and require large amounts of data. As a consequence they cannot as a general rule be performed on-line. One article proposed a modification to reduce the amount of required data (whilst maintaining computational complexity) [2], but when applied here the rate of success was nowhere near as high as that claimed. *To the best of our knowledge, no reliable, on-line, patient unspecific, computationally viable algorithm for detecting a large variety of seizures from EEG data in a clinical setting has been proposed.*

A method that has the potential of being all of these is presented in this paper. It targets pre-diagnosis detections, making the requirement for patient un-specific classification imperative. The idea is to focus on the relative *regularity* of "normal" versus "seizure" EEG above any other observable. Many techniques along this line have been tried (lyapunov exponents, entropy, correlation analysis), but the innovation lies in how regularity is detected. It is proposed that a drop in *variance* signifies more regularity in a signal. Here variance is estimated as a second or third stage in the detection process, that is, whilst pure thresholding of techniques that measure synchrony, amplitude or frequency content may miss certain seizures, their effectiveness can be increased by simultaneously tracking the variance of these estimates. More importantly, it is suggested that the exact nature of the statistic in question does not matter (so long as they are able to capture at least in part a key aspect of epilepsy) because variance drops are observed in most simple statistics during an epileptic seizure. Variance estimates have previously been used in Gotman's work [3],[7] as an aide to seizure detection, but the implications here go beyond the use of variance as a single measure. Instead, a variance drop is treated as an invariant across several statistics. This approach has the added advantage that changes in variance can be detected faster than changes in mean and as a consequence fewer data points are required to compute it.

Using this paradigm, a positive identification rate of 97.6% was achieved. Minimal pre-processing was involved, suggesting results can be improved and the idea could potentially be implemented in an on-line clinical setting.

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The remainder of this paper is organized as follows. Section II gives an outline of the methodology and mathematics employed. Section III summarizes results and concluding remarks are given in Section IV.

II. METHODS

A. Data Acquisition and Preprocessing

Data and appropriate ethical clearance was provided by St Vincent's Hospital, Melbourne, Australia. EEG was recorded using a Compumedics^{TM} Neuroscan system. Twenty-one channels were recorded from the scalp using the International 10-20 electrode placement. Data was digitized and stored using 16 bits, with sampling rate of 512Hz. Prior to sampling, an 0.15-100Hz bandpass filter was applied.

Scalp EEG records were randomly selected from a larger database and included typical events such as sleep periods, rhythms (alpha, delta, etc) and artifact. The most common artifact were eye and muscle movement, as well as (sometimes heavy) contamination of 50Hz interference. Other artifact such as cardiac rhythms may be present but could not be verified due to the unavailability of ECG traces.

A total of 83 seizures (both clinical and sub-clinical) on 15 different patients were included for testing. Seizures were classified by trained neuroscientists and ranged from a duration of 10 seconds to several minutes. Not all channels were necessarily involved in all seizures. Although there was no discrimination in the type of data used, no absence seizures were available for inclusion. However, detection of the 3Hz rhythmic bursts is well understood and results are not expected to vary were these to be included. A total of more than 170 hours were used for the current analysis. A larger database will be used for testing in the near future.

Prior to analysis recordings were placed in the Bipolar Longitudinal (BP) referencing system. This was chosen to emphasize the difference in synchronization levels between channels during a seizure. As a consequence a maximum of 16 channels were used for all tests. The only other form of preprocessing was filtering of the signal with a low pass filter, passband 0-40Hz and 80dB attenuation in the stopband. This removed 50Hz artifact, which in some cases was quite severe. No other form of artifact rejection or removal was applied (eye and muscle movements were left intact).

B. Feature Extraction

To make results less prone to the nuances of individual seizures, three statistics to quantify "typical" seizure characteristics were simultaneously tracked. The features chosen were (1) shifts in energy content, (2) regular activity within a channel and (3) regular activity between channels (i.e. synchronization). These were selected because of their intuitive relationship to the visual recognition of seizures, as well as the availability of simple linear statistics capable of characterizing them. Many other linear and non-linear techniques other than the ones presented here have been applied, but the conclusion is always the same: it is not the particular feature being targeted or the precise nature of each statistic that is important - changes in variance are observed regardless of the process. The only constraint is to select a method for which these changes occur consistently.

This section outlines the mathematics used for each of the three criteria. Each statistic is applied to T-point moving windows to each of the M channels. Details of how information from all channels is combined to be used for detection are outlined in part C. Throughout this paper the channel number is depicted by $i = 1..M$, with $M = 16$ in all cases, and discrete time within a window is given by $t = 1..T$.

Prior to processing each channel in a window was normalized to unity variance in order to achieve amplitude independence, although not all described methods require it.

1) *Energy shift:* Change in energy content is one observable during a seizure. To characterize this, a normalized cumulative frequency function was used. Let $X_i[f]$ be the magnitude of the Fourier Transform of EEG channel $x_i[t]$ for frequencies f. Here, $X_i[f]$ is calculated in 0.5Hz increments of f. Looking at a range of frequencies $f_1 \leq f \leq f_2$, a cumulative function of $X_i[f]$ is computed by

$$\begin{aligned} S_i[f_1] &= X_i[f_1] \\ S_i[f] &= S_i[f-0.5] + X_i[f] \ , \ f_1 < f \leq f_2 \end{aligned}$$

Normalizing,

$$\overline{S}_i[f] = \frac{S_i[f]}{S_i[f_2]}$$

gives a monotonically increasing function of f between 0 and 1. A record of the frequency value $F_i = f$ at which $\overline{S}_i[f] \geq R$ for the first time is kept. Changes in frequency content are reflected by changes in F_i. Values that maximized performance were: $f_1 = 0.5$Hz, $f_2 = 10$Hz, and $R = 0.7$. Windows of 1,2,3 and 4 seconds with 0,1,2 and 3 seconds overlap respectively were used. (Recall 1 second is equivalent to $T = 512$).

2) *Increased Regularity in Single Channel:* Simpler states in EEG should exhibit less erratic variation over the interval in question. To capture this, the notion of total variation was employed. For a *non-constant* discrete EEG signal $x_i[t]$, this is defined as [8]

$$V_i = \frac{\sum_{t=2}^{T} |x_i[t] - x_i[t-1]|}{\max_t x_i[t] - \min_t x_i[t]} \qquad (1)$$

where $|.|$ denotes an absolute value. The dividing term is included to normalize results and make them comparable to each other. Slow, smooth signals lower the total variation, with $V_i \geq 1$. The lower bound is achieved by functions that change monotonically between $\min_t x_i[t]$ and $\max_t x_i[t]$ over $t = 1..T$. Fast, large oscillations increase total variation: $V_i \leq T - 1$ and the upper bound achieved when $x_i[t]$ alternates between $\max_t x_i[t]$ and $\min_t x_i[t]$ at each t. A window size of 1 second with zero overlap was used for this computation.

3) *Increased Regularity Between Channels:* The cross correlation was used to characterize similarity between

channels. The normalized cross correlation between two channels $x_i[t]$ and $y_j[t]$ is given by [8]

$$C_{ij}[l] = \frac{T}{2L} \frac{| < x_i[t], y_j[t-l] > |}{\sqrt{< x_i[t], x_i[t] >< y_j[t], y_j[t] >}}$$

where $< . >$ denotes a vector dot product and $|l| \leq L$ is a discrete lag with maximum values $\pm L$. Absolute values were taken so that $C_{ij}[l]$ is always between zero and 1. A single measurable was obtained by taking the mean correlation of each channel to all others, that is,

$$C_i[l] = \frac{1}{M-1} \sum_{i \neq j} C_{ij}[l]$$

High values of $C_i[l]$ indicate high correlation or similarity between channels at a particular lag, and lower values indicate lack of correlation. $L = 200$ and $T = 512$, with zero overlap, was used for this computation.

C. Detection Strategy

The algorithm dependent values quoted are very restrictive (e.g. short windows with little overlap) and will generally not give good enough estimates of the statistic in question. However, even when longer time frames and better estimation parameters are used pure thresholding of these values does not identify all seizures. The idea presented here is that the exact value of the raw statistic is not of interest. Seizures are in general more regular in nature and a drop in the *variance* of any measure is expected during epilepsy, even if the statistics are approximations. For this reason, fewer samples are needed to give equivalent performance, decreasing computational complexity and delay times for online detection.

The issue in question is what to measure the variance of. In theory this does not matter since all reasonable statistics show a decrease in variance during a seizure, but in practice it is necessary to select something for which variance will stay relatively constant (or at least not as volatile) in periods of normal activity. False positives can be minimized this way.

To emphasize thresholds it is often more effective to take variance estimates in two stages. That is, the original statistic will record the variance of a measure at a point in time. The variability of this trace can then be tracked over time. Instead of using an unbiased variance estimator in the second stage the notion of total variation (V_i) was once again employed to detect changes in regularity. **V** is used to denote this second stage tracking of total variation, calculated as in equation 1 with 200 second windows ($T = 200$) and an overlap of 199 seconds. Because **V** is normalized and it measures the relative amount of change over an interval it is mean and amplitude independent. This is unlike the unbiased variance estimator which requires the mean of the signal as part of the computation. Fast changes in mean will often mask small changes in variance, whilst **V** is sensitive to small changes in smoothness independent of changes in mean.

Following is a description of how the variance of each of the 3 criteria were analyzed to identify seizures.

1) *Energy shift:* Normal EEG typically shows the highest concentration of energy at low frequencies (1-3Hz). Seizure activity shifts its fundamental frequency anywhere between 3-29Hz [3], with most energy concentrated in a narrower band. Because of the wide variety of seizures, as well as the evolution of the natural frequency throughout the epileptic episode, no threshold is successful in identifying all seizures. Instead, F_i was calculated for 4 different window sizes (values as previously given), and as a first stage an estimate the variance over all data was calculated at each time point. **V** was then computed for over this first stage. As expected, **V** decreased during a seizure.
2) *Increased Regularity in Single Channel:* Typical seizures are more "sinusoidal" in nature than periods of normal activity. Because windows are short and EEG frequencies are not high (especially during epilepsy), V_i is expected to decrease. The mean over all channels was computed, and **V** was subsequently tracked over this mean. Again, **V** decreased during a seizure.
3) *Increased Regularity Between Channels:* Because of the short windows and small delays chosen it is expected that $C_i[l]$ will increase (relative to background activity) for fast frequency seizures and decrease for low frequency ones. For this reason, pure thresholding on this statistic is not practical and the estimation of variance proved more successful. First, a mean of $C_i[l]$ over $i = 1..M$ was taken. A one stage estimate of variance was computed by taking the average over $l = -L..+L$ at each time point, and **V** was computed for this mean over time. Simultaneously, a two-stage approach was taken by first calculating the variance over $l = -L..+L$ and then tracking **V** over the initial variance estimate. The two approaches are as a whole complementary, but in some cases one was more pronounced than the other and better results are achieved by simultaneously tracking both.

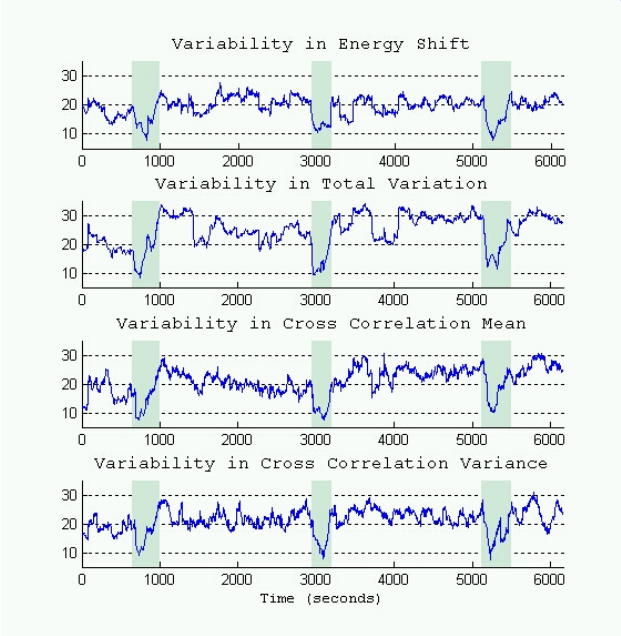
The above gives a total of 4 different statistics, calculated once a second and thresholded. An outline of results follows.

III. Results and Discussion

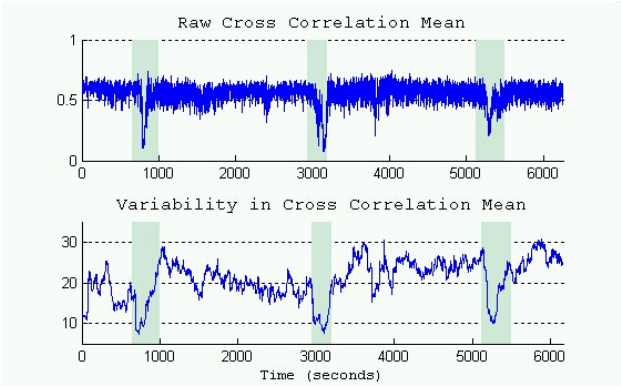
Fig. 1 shows examples of detections. Included are traces in different scenarios. It must be mentioned that not all variance estimates will decrease for all seizures. The advantage of having 4 different statistics that characterize various aspects of seizures is that a greater variety of symptoms may be detected. A single statistic is unlikely to yield a high detection rate.

The described methods were applied to over 170 hours of recording. Of the 83 seizures, only 2 were not detected by any of these techniques, giving a true positive rate of 97.6%. This is remarkable considering that virtually no prefiltering, channel selectivity or patient specific training was applied. Furthermore, in all patients at least one seizure was identified, so diagnosis was not affected significantly by this.

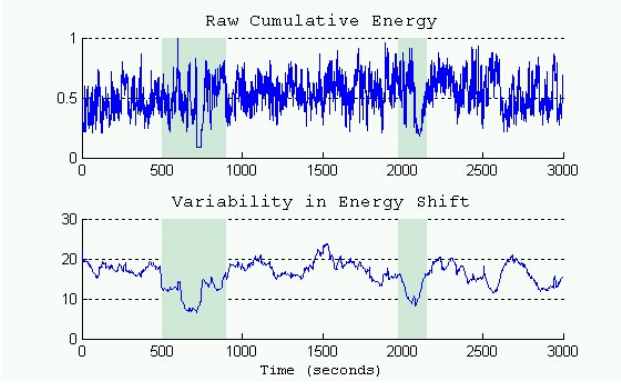
False positive detections are a problem, ranging from zero to as many as 5 per hour in some patients. On average, 3.2



(a)



(b)



(c)

Fig. 1. Example results. Seizures occur in the shaded segments (a) Three seizures detected by variability estimates in all 4 of the described methods. Note that not all seizures show as pronounced a decrease in all statistics. The above is simply a particularly good example. (b) Shows a case in which thresholding of the raw statistic would have detected the seizure. The variability estimate also makes a positive identification. (c) Pure thresholding would have had trouble detecting these seizures using raw statistics. Variability estimates are successful.

false detections per hour are expected. If at least 2 statistics must simultaneously cross a threshold to positively declare a seizure the false positive rate drops to an average of 1.3 per hour. However, performance declines and true positive rate also decreases to 81%. Further drops in performance are observed with stricter detection rules.

Significant performance improvement can be achieved with patient specific thresholding, but this would detract from the main advantage of the presented work - detection with no a priori knowledge. Instead, it is suggested that a table of probabilities of how likely it is that a seizure occurred be estimated. This would allow neuroscientists to selectively process results, with the possibility of patient-specific threshold fine-tuning after initial observations.

Optimal parameters are still being investigated to reduce false positives, including the possibility of using combined thresholds or support vector machines to classify events. Automated channel selectivity for seizures involving few channels is also being investigated.

IV. CONCLUDING REMARKS

The results presented herein indicate that excellent detection rates are possible by analyzing the variability of applied statistics as opposed to the statistics themselves. Much work remains to be done for these methods to become clinically applicable, including more extensive testing, optimal thresholding and lowering of false positives. However, the discovery that the exact nature of the applied statistics is not as important as the trend displayed by them is critical. The ideas here may be extended to other areas of EEG analysis such as brain modeling and seizure prediction algorithms.

V. ACKNOWLEDGEMENTS

The authors thank the staff at St Vincent's Hospital, Melbourne, Australia, for their help in collecting and categorizing the EEG data. Many thanks also to our colleagues The Bionic Ear Institute and Melbourne University for many interesting discussions.

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