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Frequency–moment signatures: A method for automated seizure detection from scalp EEG

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HIGHLIGHTS

- A new technique for automated seizure detection is described whereby statistical frequency–moment signatures are compared with a control group.
- Following patient-specific training, seizure detection rates are comparable to visual inspection (currently the benchmark) and false detection rates are as low as 0.020 false positives per hour.
- The technique described has the potential to be used more widely in the field of EEG interpretation and analysis, either related to epilepsy or in other situations.

ABSTRACT

Objectives: To investigate patient-specific automated epileptic seizure detection from scalp EEG using a new technique: frequency–moment signatures.
Methods: Signatures were calculated from 32 s blocks of data of electrode differences from the right (RH) and left hemisphere (LH). Discrete Fourier transforms of 15 data subsets were calculated per block per hemisphere. The spectral powers at a given frequency from the RH and LH were combined into a single quantity. The signature elements were found by subtracting normalised central moments of the subset distribution from the mean, to measure the consistency of the spectral power at a given frequency over all subsets. The seizure measure was the logarithm of the probability that a signature belonged to a control set of non-seizure signatures.
Results: Following the optimisation of signature parameters using three one-day recordings from each of 12 patients, performance was tested on a separate set of data from the same patients. The method had a sensitivity of 91.0% (total 34 seizures) with 0.020 false positives per hour (total 618 h).
Conclusions: Frequency–moment signatures promise automated seizure detection sensitivities comparable to visual identification and other published methods, with improved false detection rates.
Significance: This technique has the potential to be used more widely in EEG analysis.

1. Introduction

Epilepsy is a chronic neurological disorder characterised by the occurrence of seizures. It affects 50 million people worldwide at any one time (WHO, 2009), of which a large proportion of sufferers do not respond to available seizure control therapies. These epilepsy sufferers have to live with seizures occurring abruptly and seemingly without warning.

Non-invasive scalp EEG is recorded in long-term monitoring of epilepsy patients. Seizures and abnormal events are then identified visually from the recordings, however this is a time consuming process that can only be performed by experts. This process is critical for accurate diagnosis and choice of treatment. It has been shown that seizure detection by visual inspection has a sensitivity of 92% while detecting only 0.1 false seizures per hour (Wilson et al., 2003).

Automated seizure detection can be a valuable aid to clinicians, particularly for epileptic patients undergoing long-term monitoring (Gotman, 1990, 1997; Gotman, 1999). Many methods have been developed over the years with various approaches to the seizure detection problem. Nonlinear techniques (Schad et al., 2008; Schindler et al., 2001; Stam, 2005) as well as time–frequency analysis methods (Gotman, 1982; Gotman, 1999; Osorio et al., 1998; Sartoretto and Ermani, 1999) have been investigated. A number of methodologies have also attempted in various ways to mimic the

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human observer that reads the EEG (Deburchgraeve et al., 2008; Khamis et al., 2009). Despite a considerable research effort, current seizure detection methodologies are far from perfect with many being considered impractical due to high false detection rates (Hopfengärtner et al., 2007; Varsavsky and Mareels, 2006), however patient-specific approaches have been demonstrated to perform better than generalised methods (Chua et al., 2011).

In this work, an approach to patient-specific seizure detection is described whereby blocks of sampled electrode data are used to calculate data objects termed frequency–moment signatures. Test signatures are then compared statistically to a set of signatures from non-seizure data, and if an estimate of the probability that the test signature belongs to the control set is sufficiently low, a seizure is signalled.

Data objects known as signature images have also been used for welding fault detection (Simpson, 2007b). In that application, two-dimensional histograms of sampled welding voltage and current data formed the signatures, and whether a fault had occurred was determined by comparison with control data. Although the calculation of the signatures from the scalp EEG is very different, the statistical analysis for automated seizure detection here is based on the welding analysis with a couple of minor modifications.

The statistical analysis applies to any data object described as a vector. However there are a number of advantages to processing the data into the signature image format (if two useful axes for the signatures can be chosen), as will be shown to be the case here. Firstly, assigning the data to bins in two dimensions is useful for noise reduction and usually provides a more compact description than the original data. Secondly, simple image-processing operations, such as smoothing, can improve performance. Finally, visualisation of the signature images themselves is a valuable tool in understanding the phenomena being studied.

The following sections describe the frequency–moment signature calculations, seizure measure calculation, signature parameter optimisation, and finally testing and measuring performance.

2. Methods

2.1. Overview

Scalp EEG data was collected from epileptic patients and seizure events were marked by experienced electroencephalographers. For each patient, EEG data from electrode differences T6–P4 (right hemisphere) and T5–P3 (left hemisphere) were windowed into data blocks and filtered. The discrete Fourier transform was computed for subsets of each data block. The square root of the spectral power was smoothed and the results from each hemisphere were combined. The background spectrum was then removed and the spectrum limited to a frequency range where peaks are likely to appear during seizures. The moments of the subset distribution at each frequency were calculated and compared mathematically to a one-sided exponential distribution to yield estimates of consistency (or uniformity) within a data block for the kth moment. The signature images were then composed with the axes frequency and moment number, k. An estimate of the probability that a given signature belongs to non-seizure control data was made using Principal Component Analysis with asymmetric shifted Normal distributions fitted to each axis. Finally a seizure measure was calculated from the logarithm of the probability with modifications to reduce sensitivity.

2.2. Data collection

Continuous 24-h EEG recordings were collected from epileptic patients (8 male, 4 female, aged 19–49) with left temporal lobe epilepsy (TLE). All patients were monitored for a number of days by a nurse technician during the EEG recording and were tested clinically during a seizure. Patients were taking different antiepileptic medications, and during their inpatient EEG monitoring the doses did not remain constant but were reduced to investigate seizures for clinical purposes. Ethics approval was granted by the University of Sydney Human Research Ethics Committee and prior to enrolment in the study, patient written consent was sought.

EEG data from 21 electrodes, sampled at 256 Hz, were recorded from left temporal lobe epilepsy (TLE) patients using the Compumedics EEG system (Abbotsford, Victoria). The following electrodes were recorded: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, A1, A2, Fz, Cz, and Pz (according to the international 10–20 system of electrode placement (Malmivuo and Plonsey, 1995)). The reference electrode was on the neck or face and each electrode had an impedance range of less than 5 kΩ.

Experienced electroencephalographers inspected the 21 electrode EEG and video data visually and marked clinical and electroencephalographic events. In addition, seizure and non-seizure events were confirmed by experienced staff listening to the audified EEG (Khamis et al., 2012).

Here, an identical channel setup to Khamis et al. (2012), with four fixed channels recorded and reduced to two differences was used, as described in the following section.

2.3. Frequency–moment signatures

At the sampling rate of 256 Hz, signatures were calculated over 32 s from 8192 pairs of data points consisting of the difference between electrodes T6 and P4 (right hemisphere, RH) and the difference between the electrodes T5 and P3 (left hemisphere, LH). The blocks of 8192 pairs of data points were overlapped by 50%, resulting in a signature every 16 s. These are referred to as RH blocks and LH blocks. The standard 50% overlap results in all points having equal weighting.

The seizure events that were determined from visual and audio inspection, were used to mark each 32 s block as either seizure or non-seizure. A 32 s block was marked as a seizure if the entirety of the block was within a seizure, and marked as a non-seizure otherwise.

A 32 s block size was chosen with regard to the shortest seizure likely to be encountered. Optimising the block size could improve the performance of this method. With non-overlapped blocks, a seizure around 32 s in length would usually span two blocks and, since, as described below, the method measures consistency within each block, it would not be detected. Overlapping by 50% helps to overcome this and provides more frequent seizure measures.

EEG recordings from electrodes at the front of the head commonly contain artefacts from eye blinks and eyeball movement that are usually quite large compared to cerebral potentials. (Fisch, 1991; Reilly, 2005). This occurs far less in electrodes at the rear of the head. All data were collected from patients suffering from left temporal lobe epilepsy. For these reasons, here, fixed electrodes in the rear temporal region of the head (T6–P4 and T5–P3) were chosen for analysis. Research on audified EEG for seizure detection has demonstrated that these electrodes are a good choice (Khamis et al., 2012).

Digital pre-filtering of data is a common step in automated EEG analysis (Greene et al., 2007, 2008; Schindler et al., 2001, 2002). Here, the RH and LH blocks were filtered with a pass band between 0.5 Hz and 50 Hz and a notch filter at 50 Hz to remove baseline drift, unwanted muscle twitch and mains power interference respectively, the effects of which can mask important features of the underlying EEG signal. For the purpose of temporal lobe seizure detection, it was not necessary to preserve the entire original EEG