Journal of Neuroscience Methods 201 (2011) 262–268

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Utilising noise to improve an interictal spike detector

Alexander J. Casson[*], Esther Rodriguez-Villegas

Circuits and Systems Research Group, Department of Electrical and Electronic Engineering, Imperial College London, SW7 2AZ, United Kingdom

ARTICLE INFO

Article history:
Received 17 March 2011
Received in revised form 1 June 2011
Accepted 8 July 2011

Keywords:
Interictal spike detection
Dithering
Additive noise
Stochastic resonance

ABSTRACT

Dithering is the process of intentionally adding artificially generated noise to an otherwise uncorrupted signal to actually improve the performance of an end overall system. This article demonstrates that a dithering procedure can be used to improve the performance of an EEG interictal spike detection algorithm. Using a previously reported algorithm, by adding varying amounts of artificially generated noise to the input EEG signals the effect on the algorithm detection performance is investigated. A new stochastic resonance result is found whereby the spike detection performance improves by up to 4.3% when small amounts of corrupting noise, below 20 μV_{RMS}, are added to the input data. This result is of use for improving the detection performance of algorithms, and the result also affects the dynamic range required for the hardware implementation of such algorithms in low power, portable EEG systems.

1. Introduction

The interictal (inter-seizure) spike is an important feature of the epileptic scalp EEG: its presence aids the diagnosis of epilepsy and the localisation of the epileptic focus (Chatrian et al., 1974; Smith and Wallace, 2001). However, visual inspection of long duration EEG recordings to identify spikes is time consuming and subject to variations between interpreters. As a result there has been a large amount of research interest in the creation of automated spike detection algorithms. Casson et al. (2009) lists 70 such papers while Halford (2009) and Harner (2009) provide recent performance reviews. Despite this high level of interest however a definitive detection solution has not been found. It is clear that the task of finding a clinically acceptable trade-off between the number of events correctly detected and the number of false detections is non-trivial.

Simultaneously, in recent years there has been a large amount of interest in the development of miniaturised, wearable EEG systems for prolonged ambulatory monitoring that incorporate real-time signal processing algorithms (Casson and Rodriguez-Villegas, 2009, 2011; Yazicioglu et al., 2008, 2011; Casson et al., 2010; Verma et al., 2010; Kelleher et al., 2009; Tolbert et al., 2009). These systems aim to carry out an automated analysis of the EEG on the portable EEG device itself such that only the results of the real-time analysis need to be recorded, not the entire EEG signal. Real-time data reduction is therefore provided and in turn this can be utilised to reduce the overall power consumption of the EEG unit, reducing the EEG unit size and increasing wearability. This is provided that the implementation of the real-time signal processing algorithm itself consumes very little power (Casson et al., 2010).

In this article we propose utilising noise to improve the performance of an interictal spike detection data reduction algorithm in terms of both detection performance and hardware requirements. This is achieved through *dithering*, as illustrated in Fig. 1, where an artificially generated noise signal is intentionally added to the normal EEG signal before it is passed to the detection algorithm. Using a previously reported algorithm we demonstrate a new result whereby the algorithm performance actually improves in the presence of small amounts of introduced noise. This result can then be linked to the dynamic range, and hence power consumption, required to implement the algorithm in hardware. Both of these results are obtained without making any changes to the underlying detection algorithm itself.

2. Methods

2.1. Procedure

Based upon Fig. 1, the analysis presented here uses an existing, unmodified, spike detection algorithm (see Section 2.2) and adds an artificially generated noise signal to the raw recorded EEG before it is passed to the algorithm for analysis. The artificial noise signal has an instantaneous voltage $v_n(t)$, Root-Mean-Square (RMS) value $\sqrt{\overline{v_n^2}}$, and Power Spectral Density (PSD) $S(f)$. The aim of the analysis considered here is to asses the performance of the algorithm, in terms of the trade-off between the number of events correctly detected and the number of false detections, at different values of $\sqrt{\overline{v_n^2}}$. In addition, two different models for the PSD $S(f)$ are investigated (see Section 2.3).

[*] Corresponding author. Tel.: +44 20 7594 6297; fax: +44 20 7581 4419.
E-mail addresses: acasson@imperial.ac.uk (A.J. Casson), e.rodriguez@imperial.ac.uk (E. Rodriguez-Villegas).

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doi:10.1016/j.jneumeth.2011.07.007

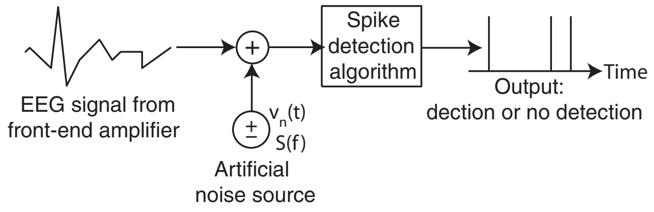
Spike detection algorithm
Time
Output: dection or no detection
EEG signal from front-end amplifier
$v_n(t)$
S(f)
Artificial noise source

Fig. 1. Dithering uses an input referred additive noise source (dither signal) to artificially corrupt an EEG recording before it is passed to a spike detection algorithm. By varying the RMS amplitude of the noise introduced the effect on the algorithm detection performance can be investigated. Here the artificial noise source has an instantaneous value $v_n(t)$ and power spectral density *S*(*f*).

2.2. Unmodified interictal spike detection algorithm

The interictal spike detection algorithm used here is that reported in detail in Casson and Rodriguez-Villegas (2009) and it is summarised in Fig. 2. The algorithm is simulated here in MATLAB and is ultimately intended for low power, online use in portable EEG units to provide real-time data reduction achieved through discontinuous recording (Casson et al., 2010). In this approach the EEG is only recorded when the detection algorithm detects a candidate interictal spike.[1] By recording a short section of EEG data around each detection, and discarding all other EEG sections, real-time data reduction is achieved.

With reference to Fig. 2, the algorithm operates by analysing each EEG channel independently with a user set detection threshold β available to control the algorithm operation. Route A through the algorithm normalises β to a value $z\beta$ to correct for broad level amplitude differences in different EEG traces and channels. Route B then extracts EEG frequency content around 8.4 Hz and uses this to determine whether a candidate spike is present by performing the comparison: $|C_5| > z\beta$? Route C provides a simple rule to reject artefacts and incorrect detections by ensuring that the normalised power in the signal band (C_5) is larger than the normalised power in an artefact band: $|C_5| > |C_{20}|$? If this condition is satisfied a detection flag is raised and a section of EEG data marked for recording with all non-marked EEG sections being discarded. A memory buffer is used to allow recording of EEG data from before and after a detection. Finally, algorithm route D is present to pass the input EEG data for recording, correcting for an inherent delay present in the other algorithm routes.

The algorithm arrangement used in this article is identical to that used in Casson and Rodriguez-Villegas (2009). Ten EEG channels (F7, F8, Fp1, Fp2, O1, O2, T3, T4, T5, and T6) are analysed in parallel with detections in multiple channels combined so that a detection in any one causes all of the channels to record a window of EEG data. The analysis in Casson and Rodriguez-Villegas (2009) is equivalent to the case for which $\sqrt{\overline{v_n^2}} = 0\ \mu\text{V}_{\text{RMS}}$: the case where no corrupting noise is added to the EEG data.

2.3. Artificial noise signal generation

Multiple methods for generating the artificial noise time series $v_n(t)$ are possible, and two methods with differing PSDs are used in this work. Firstly a white Gaussian noise model, with a uniform (flat in the frequency domain) PSD, is used. This noise, with RMS amplitude $\sqrt{\overline{v_n^2}}$, is generated in the time domain using the MATLAB `wgn` function. To ensure sampling frequency independent operation all noise signals are generated assuming a 100 Hz sampling frequency, giving noise present over a 50 Hz bandwidth. The time series is then up-sampled to match the EEG sampling frequency before being added to the EEG trace. An example resulting signal is illustrated in Fig. 3(a) for a single EEG channel. It can be seen that the artificial noise added to the EEG corrupts the baseline recording. The noise itself has a uniform spectrum up to 50 Hz and at low frequencies the EEG signal dominates over the noise.

The second noise model has a flicker distribution, where the PSD has a 1/frequency 10 dB per decade roll-off. The flicker noise time series is generated by shaping white Gaussian noise produced as above to have a 1/*f* PSD using the noise shaping filter defined in Kasdin (1995) and MathWorks (2007). An example resulting signal is illustrated in the time and frequency domains in Fig. 3(b).

2.4. Performance metrics

The algorithm performance is analysed via the trade-off between the two performance metrics of interest as the detection threshold β is varied. For real-time use a fixed value of β must be selected *a priori*, but analysing multiple values here allows the key performance trade-off to be investigated, and the user can then use this information to select the wanted operating point.

The first performance metric, the sensitivity, gives the percentage of expert marked spike events that are correctly recorded:

$$\text{Sensitivity (\%)} = \frac{\text{number of correct detections}}{\text{total number of marked events}} \times 100. \tag{1}$$

The second performance metric, the percentage of data transmitted, quantifies the amount of data reduction achieved. This metric is used over the false detection rate to be in-line with the intended data reduction role of real-time signal processing algorithms in portable EEG systems and to allow direct comparison with the results in Casson et al. (2009) and Casson and Rodriguez-Villegas (2009). The percentage of data transmitted is calculated assuming that 5 s of EEG data are recorded (2.5 s before and after) in response to each automated detection from the algorithm. For good algorithm performance high sensitivity and low percentage of data transmitted should be achieved.

The two performance metrics are generated by running the algorithm multiple times following the procedure detailed in Table 1. Eight different detection thresholds, equally spaced apart at $\beta^2 = \{0.2\text{–}0.9\}$ are used with a different trade-off between the sensitivity and percentage of data reduction transmitted being achieved for each different β value. This trade-off is then plotted on ROC-like results curves (Casson et al., 2009) in Section 3. Five values for $\sqrt{\overline{v_n^2}}$ between 0 and 40 μV_{RMS} are utilised so that the trade-off in performance is also analysed for different levels of introduced noise. This procedure is repeated separately for the two PSD noise models considered.

2.5. EEG data

The algorithm is tested by analysing a set of scalp EEG records containing expert marked interictal events. The EEG data used is summarised in Table 2 and is identical to data set *B* used in Casson et al. (2009). A total of 764 expert marked interictal events are present in 16:36:16 h of recordings from 5 patients split into 10 records. A spike is deemed to be correctly recorded if there is a detection within 2 s of an expert marking.

All EEG data uses a referential montage (FCz reference) and is high pass filtered (first-order, 0.16 Hz cut-off) before the artificial noise is added and it is passed to the detection algorithm. EEG sampling rates vary between 200 and 256 Hz and the implemented algorithm is independent of this.

[1] This article treats all interictal events, such as spikes, sharp waves, and spike-and-waves, under the umbrella term spikes. No analysis of seizure data is considered.