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TECHNICAL NOTE

Analysis of eyes open, eye closed EEG signals using second-order difference plot

Ranjit A. Thuraisingham · Yvonne Tran · Peter Boord · Ashley Craig

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Abstract An assistive technology developed for "hands free" control of electrical devices to be used by severely impaired people within their environment, relies upon using signal processing techniques for analyzing eyes closed (EC) and eyes open (EO) states in the electroencephalography (EEG) signal. Here, we apply a signal processing technique used in continuous chaotic modeling to investigate differences in the EEG time series between EC and EO states. This method is used to detect the degree of variability from a second-order difference plot, and quantifying this using a central tendency measures. The study used EEG time series of EO and EC states from 33 able-bodied and 17 spinal cord injured participants. The results found an increased EEG variability in brain activity during EC compared to EO. This increased EEG variability occurred in the O2 electrode, which overlays the primary visual cortex V1, and could be a result of the replacement of the coherent information obtained during EO by noise. A continuous measure of the variability was then used to demonstrate that this technique has the potential to be used as a switching mechanism for assistive technologies.

Keywords Second-order difference plot · Electroencephalography · Assistive technology · Central tendency measure · Spinal cord injury

R. A. Thuraisingham · Y. Tran (✉) · P. Boord · A. Craig
Department of Medical and Molecular Biosciences,
University of Technology, Sydney, PO Box 123,
Broadway, NSW 2007, Australia
e-mail: Yvonne.tran@uts.edu.au

1 Introduction

Assistive technologies are products that are designed to assist people with disabilities in daily living tasks. One type of assistive technology is the environmental control system (ECS), which is equipment that allows the individual with a disability to control aspects of their environment that are operated by electricity, such as such as the television, computer, telephones, lights, doors, and so on [7]. ECSs have been designed with switching mechanism such as using finger or arm control, voice activation, or breath activation such as the "sip and puff" [12]. However, for severe disabilities such as motor neuron disease, amyotrophic lateral sclerosis, and tetraplegia from spinal cord injury (SCI) the abovementioned switching mechanisms are not always feasible. This has lead to research investigating translating brain signals into operational commands (without requiring physical movement), such as brain–computer interfaces (BCIs) for technical devices such as an ECS [13]. Our research investigates a system that utilizes changes in the electroencephalogram (EEG) alpha rhythm (8–13 Hz) during eye closure as a switch for an ECS [5, 9]. This system has been developed so that the severely disabled are able to control "hands free" any electrical devices in the user's environment. The ability for this system to switch has been evaluated in a clinical trial and shown to be efficacious with severely disabled people in their own homes [5]. One major advantage such a system has over many BCI currently being researched is the simplicity in the switching mechanism. Current BCIs requires a lot of time to learn or practice mental concentration as it is common to use motor imagery as the "switching" mechanism [11] in order to improve its effectiveness. Other problems involving BCIs also requiring research is the need to improve classification

techniques [14] in attempt to reduce errors and improve learning time. Here, users are only required to be able to open and close their eyes on demand and thus there is very little learning time necessary.

Previously, this system relied on the spectral analysis of the EEG signal using Fast Fourier Transforms. This method required calculation of a threshold EEG level to trigger from the change in alpha wave activity during eyes open (EO) to eyes closed (EC) and therefore required baseline EEG setup of each individual [10]. To improve upon this, other alternative methods for processing the complex EEG signals using nonlinear techniques such as fractal dimension has also been conducted and shown to result in improved switching rates in the system without the need of baseline setup [6]. This method depended on changes in the fractal dimension detected from an EO to EC state. However, it is imperative that we continue to explore a range of innovative EEG processing techniques in order to develop the most ergonomic switching algorithm for use in an ECS. Consequently, in this paper we present switching results for a novel technique used in continuous chaotic modeling, this method provides an alternative "switching" mechanism for the system and can be used, instead of or in conjunction with, the spectral and fractal dimension techniques. The three techniques each measure unique aspects of the alpha signal during eye closure. In the linear spectral method, the increase in the spectral amplitude of the alpha band is measured when eye closure takes place. In the fractal dimension method, the irregularity change that arises from large scale fluctuations that accompanies eye closure is estimated, however this method avoids the short time noisy fluctuations. This current method, using second-order difference plots measures changes in irregularity that arises from short time noisy fluctuations. It is important to explore many switching methods as there are large variations in brain signals from person to person, as well as differences observed between brain signals of able-bodied compared to spinal cord injured [1, 16]. To create an effective environmental control unit the technology must be applicable to as many users as possible, especially those from a clinical population such as spinal cord injured.

This novel technique was employed to detect the differences in the EEG time series between the EC and EO states. The technique measures the degree of variability seen in a second-order difference plot, and quantifies it using central tendency measure (CTM) [4]. A second-order plot is similar to a Poincare plot where instead of plotting successive values of the time series against each other, successive differences in the time series are plotted against each other. These differences approximate to the first derivatives in a uniformly sampled time series. The CTM measures the variability in this plot. This degree of variability has been shown to be useful in the study of chaotic systems and has been used in classification problems involving separation of congestive heart failure patients from normal patients [4]. It has also been used in the study of hemodynamics in biological systems [3] and applied to EEG signals for the detection of determinism in the short time series [9].

The aim of this study was to determine whether significant differences between the EO and EC EEG time series can be detected using second-order difference plots for a fixed sampling rate. Furthermore, given the known differences in EEG between non-neurologically disordered and people with SCI, it was also important to investigate the ability of second-order difference plots in detecting EEG changes in a sample of SCI persons relative to able-bodied persons. The second-order difference plots are constructed directly from the one dimensional EEG time series [4] and not from the attractor trajectories [9]. In the latter study, second order plots using attractor trajectories were used to detect determinism in short time stationary EEG series. The time series used in this current study has epochs of EO and EC episodes separated at fixed times, corresponding to when eye closure and opening takes place. The sampling rate is constant throughout the time series. The variability seen in the second-order difference plots and quantified by CTM is then used in the analysis. A time series where the approximate first derivatives are changing smoothly will have a low CTM value while an irregular time series will have a higher CTM value. Changes in the frequency content and degrees of freedom are possible causes for any differences in CTM values between the two mental states.

2 Methods

2.1 Second-order difference plot and CTM

In the Poincare plot, each sample value $x(n + 1)$ is plotted against $x(n)$ in a time series [2] where $x(n)$ is the value of time series at the discrete time n. It displays the correlation between consecutive values in the time series. In the second-order difference plot, $[x(n + 2) - x(n + 1)]$ is plotted against $[x(n + 1) - x(n)]$. It is a plot of successive rates against each other and gives a graphical representation of the rate of variability $[x(n + 2) - x(n + 1)]$ versus $[x(n + 1) - x(n)]$. It shows the rate of variation of successive rates. For continuous data as the sampling interval decreases, the rates scale appropriately and approach the result of the continuous data. Therefore, provided the sampling interval is small, the differences will approach a scaled rate of the continuous function where the scaling factor is the sampling frequency. In this study the same sampling frequency is used both for EC and EO.

The CTM quantifies the variability seen in the second-order difference plot. It is computed by selecting a circular region of radius r, around the origin, counting the number of points that fall within the radius, and dividing by the total number of points. Let n be the total number of points and r the radius of the central area. Then,

$$\mathrm{CTM} = \frac{\sum_{i=1}^{n-2} \delta(d_i)}{n-2}$$

$$\delta(d_i) = \begin{cases} 1 \text{ if } \left([x(i+2)-x(i+1)]^2 + [x(i+1)-x(i)]^2\right)^{0.5} < r \\ 0 \text{ otherwise} \end{cases}$$

for each radius r, CTM provides the fraction of the total number of points that lie within it. Sample values, which are within a small radius r, correspond to successive rates that are small. These reflect the low frequency components or the slow ascending, descending part of the function in the time series. Sample values that correspond to high r are those of high frequency components or the rapid ascending, descending part of the function in the time series. For a particular radius r, CTM counts the number of successive rates that have all sign combinations, without any distinction. In order that we do not count sample values corresponding to spurious high frequency noisy components, the radius r, when the CTM reaches a value 0.90 is chosen as a measure of the total variability of the system. This measure of central tendency was found to be better than the measurement based on the average length,

$$\frac{1}{(n-2)} \sum_{i=1}^{(n-2)} \left\{ [x(i+2)-x(i+1)]^2 + [x(i+1)-x(i)]^2 \right\}^{0.5}$$

which tends to neglect the fine structure distribution.

2.2 Participants and EEG recordings

The EEG data from 33 able-bodied participants (17 males and 16 females) with mean age of 38.4 years (SD = 10.3) and 17 SCI participants (16 males and one female) with mean age of 33.7 years (SD = 10.1) were used for this study. The SCI group was a mixture of tetraplegic (n = 7) and paraplegic (n = 10) participants mostly with complete breaks (n = 2 incomplete). All participants consisted of volunteers from the community. All participated in a structured interview immediately prior to the study in order to determine health status. Subjects were included only if they were overtly free of viral or bacterial disease, and reported no prior psychopathology. Participants were also included if they were not taking any medication that could potentially affect the recording of the EEG. The study was approved by the institutional research ethics committee and participants were only entered into the study after informed consent.

Able-bodied EEG data was collected using the Neurosearch-24 data acquisition system (Lexicor Medical Technologies, Boulder, CO, USA). The SCI EEG data was collected using the Biosemi^{TM} Active-OneSystem. All EEG signals were recorded following the International 10–20 Montage system covering all the cortical areas of the brain. All silver/silver chloride electrodes were referenced to linked earlobes and impedances were kept below 8 kΩ. EEG data signals for the Neurosearch-24 were acquired at a sampling rate of 128 Hz and the gain set at 16K to ensure waveform resolution was not lost. For the Biosemi system, signals were acquired at a sampling rate of 256 Hz which was down sampled to 128 Hz to match the Neurosearch-24 data. A low-pass filter was set at 50 Hz to reduce any electrical noise. In both the able-bodied and SCI group only EEG activity from the cortical site O2 was used. Data was similar for the O1 site. An occipital site (O2) was chosen for two reasons: (1) alpha activity is usually larger in the occipital regions as it is linked with visual perception and (2) there is reduced artefact (e.g., ocular muscle activity) in this region compared to frontal scalp regions [6]. All subjects were assessed for their EEG activity in sessions of 3 min, which included 30 s of EO, 30 s EC, consecutively for the 3 min. From the 30 s periods, 10 s of data (1,280 points) was used for the second-order plots. Only the immediate first 10 s following EO or EC was used as we wanted to ensure that the EO, EC states were not contaminated with artefact. All subjects were tested in a quiet laboratory free of auditory stimulation and all subjects were tested when alert and subjects were only tested over a short period preventing them from becoming fatigued.

3 Results

Figure 1 shows the second difference plot of the EEG data of an able-bodied and SCI participant in the EO and EC states. In the EC case the plot is more elongated than when the eyes are open, which is fatter at the centre. Figure 2 shows the CTM plot for this able-bodied and SCI participant in the EO and EC states whose second-order difference plots are shown in Fig. 1. The CTM clearly distinguishes the two states. There is more variability when eyes are closed than when open. The plot shows that for a particular value of CTM, which represents a fractional value of the total number of samples, there are more samples having high successive rates when eyes are closed than when open. The radius r, when the CTM reaches a

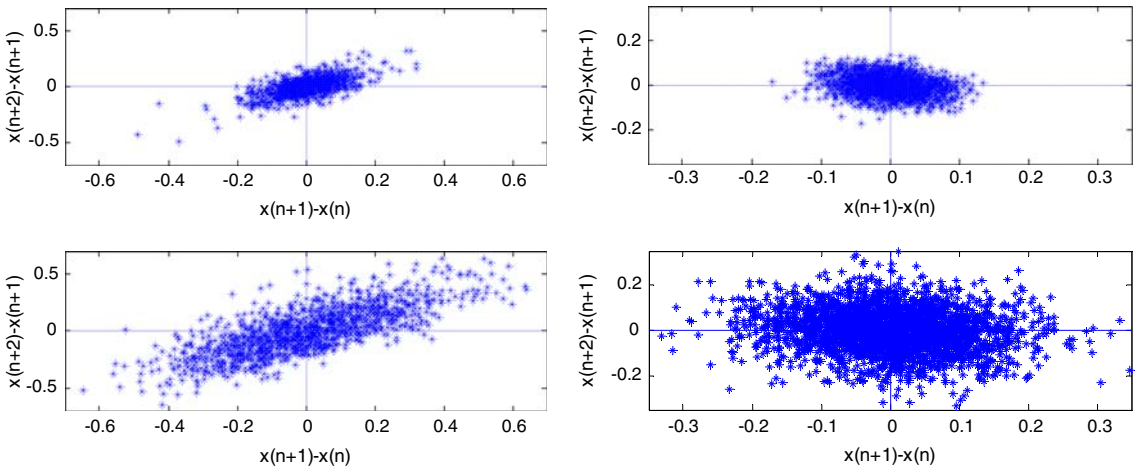

Fig. 1 Second-order difference plots EEG time series. *Top panel* corresponds to a subject with eyes open and *bottom panel* to a subject with eyes closed. The *left* and *right panels* corresponds to an able-bodied and SCI subject, respectively

value 0.90, chosen here as a measure of the total variability of the system, is higher for EC compared to EO. To test for within group differences between the EO and EC states for both the able-bodied and SCI groups, repeated measures ANOVA was performed on the r values when CTM reached 0.90 (dependent variable) for each group. The three EC and EO measures were averaged to produce one EC and EO value for each subject. The results showed that the EO and EC states were significantly different for the able-bodied group, $F(1,32) = 68.48$ ($p < 0.01$) and for the SCI group $F(1,16) = 44.88$ ($p < 0.01$).

To test the effectiveness of this technique as the basis for detecting EC states and thus as a switch for the ECS brain interface for SCI people, we tested the difference in the r value when CTM reached 0.90 from EO to EC. Let r_d (radius differences) be defined by:

$$r_d = r(0.90,\ \text{eyesclosed}) - r(0.90,\ \text{eyesopen}),$$

where $r(0.90,\ \text{eyesclosed})$ and $r(0.90,\ \text{eyesopen})$ are the values of r for EC and EO, when CTM reaches a value of 0.90. In Fig. 2, the value of r^d is positive in going from EO to EC. In order to check the viability of using this information to detect changes from EO to EC, the value of r^d is evaluated for the data from the able-bodied and SCI participants. Since each participant had three consecutive measures of EO, EC an increased sample size of 99 combinations of EO and EC intervals in the able-bodied group and 51 EO and EC combinations in the SCI group were available for analysis. The three EO and EC combinations from each participant were done as part of a data collection procedure to check the viability of using EO, EC as a switch strategy. The results are shown in Fig. 3. In this figure, successive sets of three consecutive points, beginning from 1, correspond to a participant. The results indicate that r^d is negative in only 18.2% of the cases in the able-bodied group and 9.8% in the SCI group. In the above analysis it is assumed that there is no overlap between the EO and EC regions.

To examine the use of the above result as a switch when eye closure takes place, the value of $r(0.90)$ was evaluated every second using the previous 10 s of EEG data. This was carried out after an initial lag of 10 s. The result of this study on a subject whose EEG time series has three

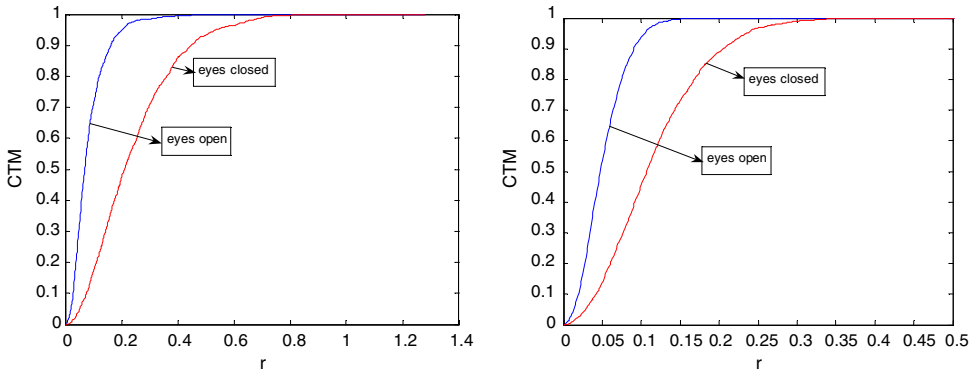

Fig. 2 Central tendency measure as a function of r for eyes open and eyes closed for the above representative able-bodied (*left*) and SCI (*right*) subjects

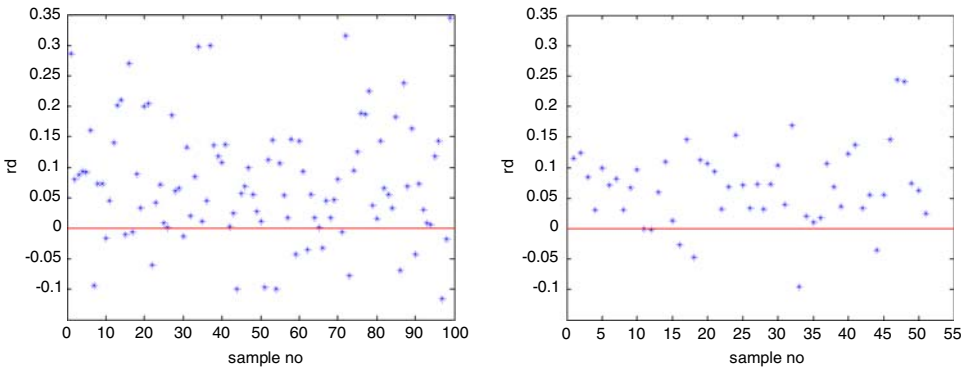

Fig. 3 Values of r_d for able-bodied (*left*) and SCI (*right*) subjects. Sample number represents the three EO/EC differences in each participant

consecutive intervals of EO and EC is shown in Fig. 4. In this EEG time series, the participant closes his/her eyes at t = 22, 62, and 102 s. The result shown in Fig. 4 indicates a sharp change in r (when CTM = 0.90) close to the switching points. Exploiting the sharp change observed during moments where EC occurred the times at which this change in gradient occurred were determined for the 150 eye closure samples for all subjects. Overall the average switching time for the able-bodied group using this method was 5.79 s (SD = 3.58) and for the SCI group this decreased to 3.14 s (SD = 1.32). The discrepancy in the actual time of eyes closure and the change in gradient (where potential switch times will occur) for these samples are shown in the right of Fig. 4. The percentage of the samples having a switch time of less than 5 and 10 s are 68.7 and 94, respectively. Although there were only very few switches that occurred after 10 s following eye closure (n = 7), there are a large number of potential false positive switches as shown with a number of negative "switch error" times (36 out of 99 in the able-bodied group and 30 out of 51 in the SCI group).

4 Conclusion

The change from EO to EC EEG series was studied using second-order difference plots in order to assess its usefulness as a basis for a "hands free" control system for the severely disabled. To quantify the variability in the change from EO to EC, the CTM was used. Significant differences occurred for the r values at CTM = 0.090 for both groups of subjects between the EO and EC states, demonstrating that the second-order difference plot strategy would be capable of distinguishing reliably between EO and EC for able-bodied and SCI persons. This is an important finding given that SCI people have been shown to have significantly altered EEG patterns in the 8–13 Hz range (alpha activity) [1, 16].

The analysis is verified further by examining a larger data set of 150 combinations of EO and EC EEG time series obtained from all 50 subjects. The time taken to switch are comparable to the previous two techniques (spectral and fractal techniques), on average the current method produced switching times of 5.79 s (SD = 3.58) for able-bodied participants. In the same group using the spectral and fractal technique as shown in a previous paper [6] this was 4.36 s (SD = 4.70) and 5.64 s (SD = 4.32), respectively. Although overall time to switch using the second order technique is comparable, it produced zero false negatives (no switching when eyes were closed), however, this did result in substantially higher amount of false positive switches (switching when eyes were opened). There were 36 incidents of false positive switching from 99 switches compared to four using the spectral technique and three using the fractal technique [6]. The failure rate from false positives could be attributed to possible overlap of EO

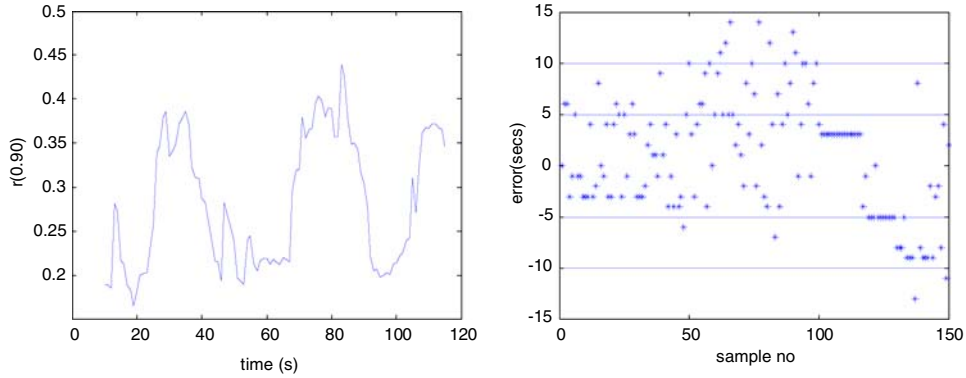

Fig. 4 Plot of r (0.90) for 10 s of data every second after an initial lag of 10 s for an EEG series where eye closure occurs at t = 22, 62, and 102 s (*left*) and error/discrepancy in switch time in seconds for different eye closures (*right*). In the figure on the right sample number represents the three EO/EC differences in each participant from both able-bodied and spinal cord injured combined

and EC intervals as there were many false positive switches recorded at 1–3 s prior to eye closure (26 of the 36 incidents). This needs to be improved by improving the method we are using to produce a continuous measure of the second order variability. Other possible reasons for false positive switching include raised alpha waves during EO as well as the presence of artifact or noise from various sources. The presence of extraneous peaks at positions other than that at eye closure and absence of a strong peak at eye closure are some of the problems encountered in determining accurate estimates of the switching times. Inspite of these problems switching time of less than 5 and 10 s were obtained in 68.7 and 94% of the samples, respectively.

Examination of the EEG data of a representative subject with EC and EO using the above method showed greater variability in the second-order difference plots for when the eyes were closed compared to when they were open. The increased variability observed in the second-order difference plot during EC is more than likely an indication of changed brain activity. This change in activity could be a result of change in frequency content or an increase in the degrees of freedom in the EEG signal collected from the cortical site O2, which overlays the primary visual cortex V1 [15]. It is possible that on closing the eyes, the continuous coherent information from the external world is replaced by noise, giving rise to higher variability. In addition, higher variability could have been attributed to the larger amplitudes and larger variation in amplitudes during EC.

Previously, when examining the fractal dimension using the Higuchi algorithm [8] we found that during eye closure there was a decrease in the signals irregularity rather than an increase in variability. The decreased irregularity was probably due to the increased alpha observed. A possible explanation as to why there is a contradiction to the level of variability in the signal could be due to the differences in the methods used. In fractal dimensions the method used evaluated the irregular time series via the calculation of the length of the curve [8]. It provided a better alternative to measuring the frequency exponent in the power spectrum by providing a stable index avoiding the short time noisy fluctuations. It measures large scale fluctuations. On the other hand, the second order plot measures the angle variations in the time series, estimated via the CTM. These angle variations are affected by the noisy short time fluctuations [4, 9]. Thus unlike Higuchi fractal dimension methods it provides a measures of the noisy short time fluctuations present in the time segment. During the time of eye closure the increase in noise could be due to loss of receipt of coherent information. This increases the CTM.

There is still room for further improvements to overcome some of the aforementioned problems. The presence of extraneous peaks at positions other than that at eye closure and absence of a strong peak at eye closure are some of the problems encountered in the detection procedure. However, these problems also occur in other methods which employ fractal dimension [6] and spectral power [10]. Each technique explored to date has brought unique aspects to detecting switches. Spectral technique has the highest false negatives, and requires baseline adjustments for each individual but provided the fastest switching times, fractal technique improved upon the errors and the second-order difference plots reduced the occurrence of false negatives. It is therefore possible that not one but a fusion of these different methods which employ fractal dimension, spectral power, second order difference variability may prove to be very effective in the design of a hands free switching mechanism. This work is under consideration. Nevertheless the initial results are encouraging which indicate the possibility of developing another switching mechanism for eye closure based on the variability measured from the second-order difference plot. The results of the work described in this paper have demonstrated that the difference in the variability between EC and EO as measured using the second-order difference plot, show significant potential to be used as the basis for a "hands free" switching mechanism for the severely disabled.

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References

1. Boord P, Siddall P, Tran Y, Herbert D, Middleton J, Craig A (2007) Electroencephalographic slowing and reduced reactivity in spinal cord injury neuropathic pain. Spinal Cord. doi: 10.1038/sj.sc.3102077
2. Brennan M, Palaniswami M, Kamen P (2001) Do existing measures of Poincare plot geometry reflect nonlinear features of heart rate variability. IEEE Trans Biomed Eng l48:1342–1347
3. Cohen ME, Hudson DL, Anderson MF, Vazquez C (1993) Blood flow data exhibit chaotic properties. Int J Microcomput Appl 12:82–87
4. Cohen ME, Hudson DL, Deedwania P (1996) Applying continuous chaotic modeling to cardiac signal analysis. IEEE Eng Med Biol Mag 15:97–102
5. Craig A, Moses P, Tran Y, McIsaac P, Kirkup L (2002) The effectiveness of a hands-free environmental control system for the profoundly disabled. Arch Phys Med Rehabil 83:1455–1457
6. Craig A, Tran Y, Craig D, Thuraisingham R (2005) Improving correct switching rates in a "hands-free" environmental control system. J Neural Eng 2:L9–L13
7. Craig A, Tran Y, McIssaac P, Boord P (2005) The efficacy and benefits of environmental control systems for the severely disabled. Med Sci Monit 11:RA32–RA39
8. Higuchi T (1988) Approach to an irregular time series on the basis of the fractal theory. Physica D 31:277–283

9. Jeong J, Gore JC, Peterson BS (2002) A method for determinism in short time series, and its application to stationary EEG. IEEE Trans Biomed Eng 49:1374–1379
10. Kirkup L, Searle A, Craig A, McIsaac P, Moses P (1997) EEG-based system for rapid on–off switching without prior learning. Med Biol Eng Comput 35:504–509
11. Mahmoudi B, Abbas E (2006) Electro-encephalogram based brain–computer interface: improved performance by mental practice and concentration skills. Med Biol Eng Comput 44:959–969
12. Mason SG, Birch GE (2003) A general framework for brain–computer interface design. IEEE Trans Neural Syst Rehabil Eng 11:70–85
13. Neumann N, Kubler A (2003) Training locked-in patients: a challenge for the use of brain–computer interfaces. IEEE Trans Neural Syst Rehabil Eng 11:141–144
14. Sun S, Zhang C (2006) Adaptive feature extraction for EEG signal classification. Med Biol Eng Comput 44:931–935
15. Tong F (2003) Primary visual cortex and visual awareness. Nat Rev Neurosci 4:219–229
16. Tran Y, Boord P, Middleton J, Craig A (2003) Levels of brain activity 8–13 Hz in persons with spinal cord injury. Spinal Cord 42:73–79