Journal of Medical Engineering & Technology, Volume 27, Number 4, (July/August 2003), pages 145–148

Taylor&Francis
healthsciences

Symbolic dynamics applied to optokinetic nystagmus signals

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In this study symbolic dynamics is used to analyse the time evolution of the optokinetic nystagmus (OKN). The inter-saccadic nystagmus differences are transformed into a sequence of three equally numbered letters (symbols) which represents the temporal changes in the inter-saccadic signal: (a) a fall in the temporal change, (b) no changes and (c) a rise in temporal change. The complexity of the data series was then calculated as the entropy of the word length three probability distribution of the symbol sequence. The method was applied to OKN signals from ten healthy subjects and ten patients suffering from vertigo (four tests on each subject) and to 40 artificial white noise data series of the same length as the symbolic representation of the OKN data. Applying Student's t-test showed a statistically significant lower mean entropy value ($p < 0.05$) for the patients.

Introduction

One of the tests used in the clinical evaluation of patients suffering from vertigo (dizziness) is the optokinetic test [1]. Presented with a moving image, the eyes respond with a movement in the same direction as the image, interrupted by quick resetting phases. These reflexive, rhythmic eye movements, named optokinetic nystagmus (OKN), interact with the vestibulo-ocular reflex and the smooth pursuit function to hold objects steady on the retina. Despite this relatively simple function, the optokinetic nystagmus signal exhibits a complex behaviour. The question is whether the never-ending variation of slow and fast nystagmus phases is a result of underlying physiological regulating mechanisms, or just random variations.

An earlier study [2] showed a statistically significant lower mean correlation dimension value for OKN signals from a group of vertigo patients compared to a group of healthy subjects, and it was discussed if this could reflect a reduced functionality of the vestibular system in the vertigo group; a reduced ability to rapidly regulate and adapt to the ever changing environment. The present study is a re-examination of the same data, and the goal was to see if the method of symbolic dynamics confirms the results, which would support the hypothesis of a reduced complexity of the OKN signals for the patients suffering from vertigo. Since the method of symbolic dynamics applied in this study is much easier to implement, and less computer intensive than the correlation dimension estimation procedure used in the previous study [2], it is preferable to use this method when analysing the nonlinear properties of the OKN dynamics.

To my knowledge symbolic dynamics has not yet been applied to OKN data, but the clinical implication of the method to other time series data, such as electrophysiological data from the human heart, has been published [3].

Material and methods

Subjects

The OKN-signals were recorded in ten healthy subjects (mean age = 27 years, range 22 to 36) and ten patients suffering from vertigo (mean age = 57 years, range 21 to 75). The patients' diagnoses are given in table 1.

Recording technique

Horizontal eye movements were recorded with two electrodes (Ag–AgCl skin electrodes) placed lateral to each eye, and a reference electrode at the center of the forehead. The signal was amplified (10 s time constant and an upper cut-off frequency of 30 Hz) and digitized into an IBM-compatible computer, using 12 bit A/D resolution and 100 Hz sampling frequency (sampling time $\tau_s = 0.01$).

Optokinetic stimulation and registration

Optokinetic nystagmus was obtained by stimulating the visual field with 3.75° width vertical light stripes

Table 1. The different types of vertigo.

Patient	Vertigo types
1	Post-traumatic encephalopathia
2	Barotrauma of the left ear
3	Chronic otitis with fistula; reduced function of the left vestibular organ
4	Progressive cerebellar atrophy with ataxia
5	Acoustic neurinoma of the VIIIth cranial nerve on the right side
6	Vestibular neuronitis, no sequel
7	Other vestibular etiology
8	Central etiology other than vascular
9	Central vascular lesion
10	Central vascular lesion

Journal of Medical Engineering & Technology
ISSN 0309-1902 print/ISSN 1464-522X online
http://www.tandf.co.uk/journals
DOI: 10.1080/0309190021000059696

separated by 11.25° width dark stripes. A slit projector presented the stripes on the inside of a hemispherical screen (100 cm in diameter). The subjects were sitting in front of the screen in a darkened room and were instructed not to follow the stripes with their eyes, but to focus their vision on the screen, allowing the optokinetic reflex to control the eye movements.

Four registrations were performed on each subject according to the direction and the velocity of the movement of the stripes: Left 30° s^{-1}, Right 30° s^{-1}, Left 60° s^{-1}, Right 60° s^{-1}. Between each test the subject was resting for a minimum of 60 s in a darkened room.

Evaluating the OKN time evolution

The procedure used for computing the complexity of the OKN time series is summarized in the following steps, and exemplified on a typical data series (figure 1 (*a*)).

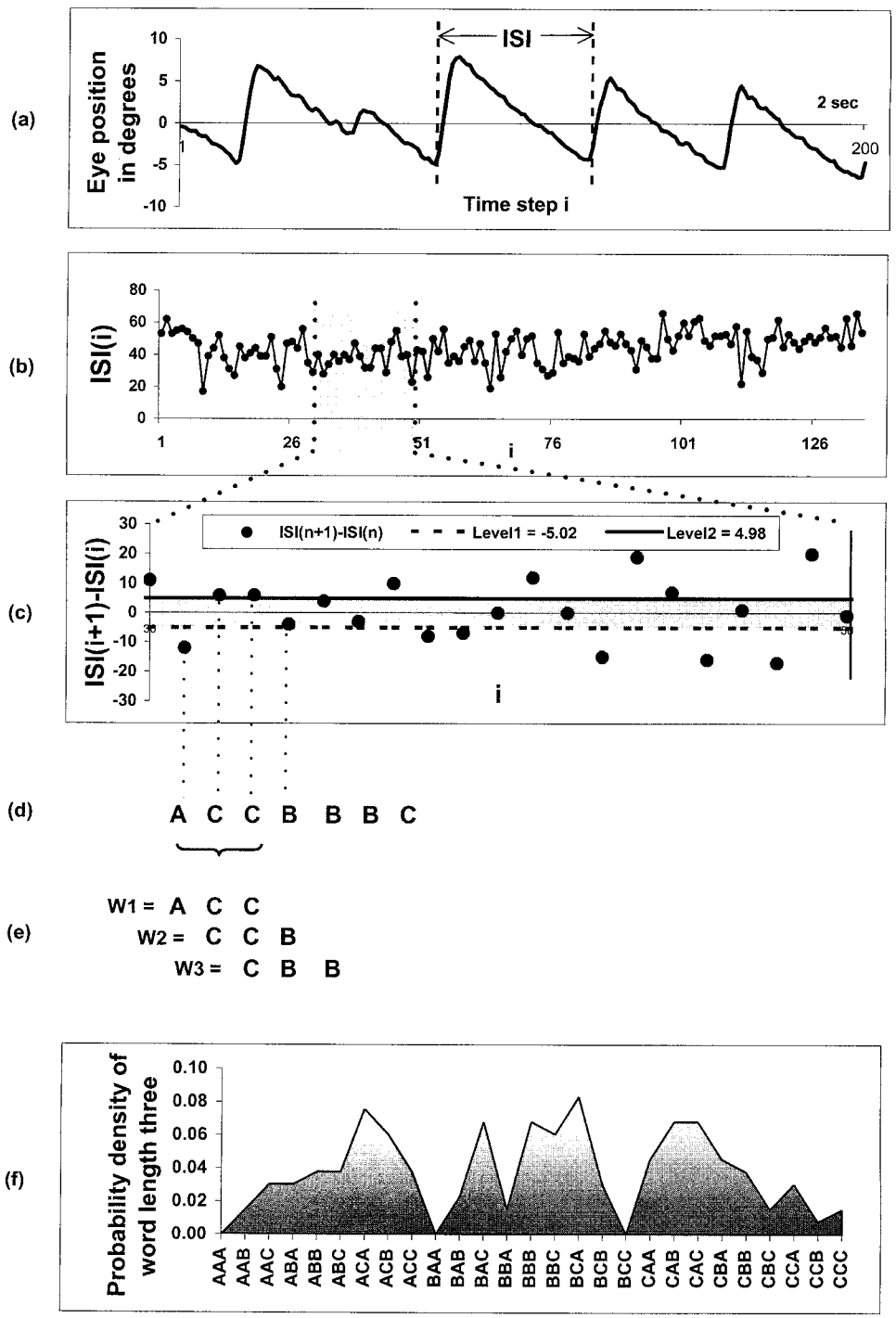

Figure 1. (a) A to second registration of an optokinetic time series. Upward direction represents eye movement to the right, downward to the left. In (b) the inter-saccadic nystagmus interval (ISI) is shown, (c) the ISI differences, (d) the time series sequence of symbols, (e) the world length three series and (f) shows an example of the probability density distribution of word length three.

(1) Find the inter-saccadic nystagmus interval (ISI) sequence $\{x_i\}_{i=1}^{n}$ (figure 1 (*b*)).

(2) Calculate the ISI differences, y_i (figure 1 (*c*))

$$\{y_i\}_{i=1}^{n-1} = x_{i+1} - x_i.$$

(3) Detect the two levels, which divide the data into three equally numbered data sets† (figure 1 (*c*)).

(4) Transform y_i into the time series sequence of symbols s_i (figure 1 (*d*))

$$\{s_i\}_{i=1}^{n-1} = \begin{cases} C: & y_i > level2, \\ B: & level1 > y_i \leq level2, \\ A: & y_i \leq level1. \end{cases}$$

(5) Find the word length three series w_i (figure 1 (*e*))

$$\{w_i\}_{i-1}^{n-1-2} = s_i s_{i+1} s_{i+2}.$$

(6) Compute the probability density distribution, p_k, of wordlength three ($\sum_{k=1}^{\#bins} p_k = 1$, where $\#bins = \#symbols^{(\#word\ length)} = 27$) (figure 1 (*f*)).

(7) Calculate the normalized information entropy, *I*, of the probability distribution

$$I = -\frac{1}{\log(27)} \sum_{k=1}^{27} p_k \log(p_k), \quad 0 \leq I \leq 1.$$

The procedure was also applied to 40 computer generated data series with white noise properties of the same length as the ISI data sequence.

The mean value of the symbol sequence length $(n-1)$ for the 80 OKN registrations was 148.

Results

Student's *t*-test was used to compare the mean values (see figure 2) of the entropy parameter for the three groups of data series: the patients ($n=40$), the healthy subjects ($n=40$) and the artificial random data (n = 40). The result showed a statistically significant lower mean entropy value, *I*, for the patient group (defined by a p value <0.05): healthy compared to patients ($p=0.0073$) and random compared to patients ($p=0.0003$). No significant differences were found for the entropy parameter between the healthy subjects compared to the random data ($p=0.584$).

† It is not always possible to divide the data into three equally numbered data sets. Practically the solution is to find the levels with the best match.

Discussion

Looking for a pattern in very short time series, e.g. $n<200$, is almost impossible when the data series is digitized with 12 bit A/D resolution. 12 bit resolution means that the data can take 4096 (2^{12}) different values if one makes use of the full dynamical range. In a time series of $n<200$ data points one can easily end up with n unique values. The method of symbolic dynamics is a coarse graining technique, which reduces the detailed description of the data series, but still represents the global dominant trend of the system dynamics. In this study the inter-saccadic nystagmus interval is modelled as three different qualities of the systems dynamics: (a) reduced tempo, (b) no changes and (c) increased tempo. The complexity of this symbolic representation of the dynamical behaviour was statistically reduced for a group of patients suffering from vertigo. This reduction in physiological complexity was earlier reported in [2]. However, the procedure for calculating the correlation dimension described in the referred study is complicated, and the result sensitive to the choice of model parameters. The procedure described in the present study is, in contrast, very simple to implement, and gives a unique result which can easily be replicated for evaluation. This is crucially important when the purpose is to develop a new diagnostic technique.

A regression analysis applied independently to the patients and to the healthy subjects, revealed no statistically significant relation between age and the entropy parameter.

The reason for applying the method of symbolic dynamics to the ISI differences, and not directly to the ISI, was to omit longer periods of the same symbols, as a result of drift in the ISI tempo.

Conclusion

The procedure of symbolic dynamics described in this paper (which is a modification of the method published by Voss *et al.* [3]), is easy to implement and particularly

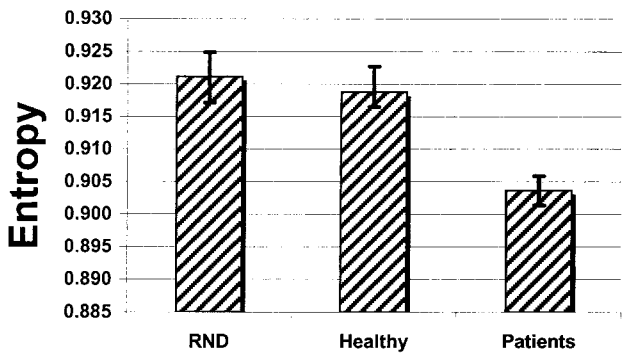

Figure 2. The mean and standard error of the entropy, I, for the three groups of data series: the random data, the healthy subjects and the patients.

useful for identifying patterns of information in short time series from dynamical systems. The same result as in [2], of reduced complexity of the OKN dynamics for patients suffering from vertigo, was obtained.

It is too early to say to which underlying physiological mechanism of the vestibular system the algorithm is sensitive. The clinical specificity will therefore first be revealed when the procedure is applied to large representative vertigo groups with known diagnosis.

Acknowledgment

I thank Assistant Professor Anne Brit Sørsdahl for helpful comments in the preparation of this manuscript.

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