

# Short-term information pattern in optokinetic nystagmus amplitude time series

T. Aasen\*, F. Goplen and S.H.G. Nordahl

*National Center for Vestibular Disorders, Department of Otorhinolaryngology/Head and Neck Surgery, Haukeland University Hospital, Bergen, Norway*

Received 18 April 2012

Accepted 18 March 2013

**Abstract.** In this paper we analyzed optokinetic nystagmus (OKN) signals for underlying information patterns. Fourteen OKN signals were recorded in five healthy subjects. First, we tested the correlation between nystagmus slow and fast phases. Previously, it has been suggested that the correlation is higher between the amplitude of the slow phase and the following fast phase, compared to the correlation between the fast phase and the following slow phase. However, we found no such difference. This is in agreement with the view that the saccade performed by the eye is not determined by the previous slow phase, but is free to move voluntarily in order to focus on an object of interest. Second, we analyzed the information entropy contained in the sequence of optokinetic nystagmus amplitudes, and found a short-term information pattern. Further analysis of these patterns could eventually lead to more knowledge about the vestibular and oculomotor systems.

**Keywords:** Optokinetic nystagmus, vertigo, symbolic dynamics, information pattern

## 1. Introduction

The purpose of this study was to analyze information patterns in optokinetic nystagmus (OKN), which is a reflexive mechanism of global retinal image stabilization during full-field pattern movements. The primary inputs to this reflex are from subcortical visual pathways.

Vision plays a central role in our interaction with the environment. In the human eye, the highest density of photoreceptors can be found in the fovea centralis. For maximal visual acuity, the eye must move constantly so that objects of interest are projected on the fovea. Optokinetic eye movements enable the eye to track the movement of objects across the visual field. Similarly, when presented with a moving image, the eyes respond

with a movement in the same direction as the image, interrupted by quick resetting phases [5]. These reflexive, rhythmic eye movements, which are called optokinetic nystagmus, interact with the vestibulo-ocular reflex and the smooth pursuit function to hold objects steady on the retina. The quick resetting phases generally move the eye to a more central position; however, it is not known how their amplitudes are regulated.

Results from an earlier study by Chun and Robinson [3] suggested a high correlation between slow phase amplitudes followed by fast phase amplitudes and a lower correlation between fast phase amplitudes followed by slow phase amplitudes in cats. This implies that the corrective fast phases are determined by the previous slow phases. This study is often cited and it is of interest to clarify if their findings are also valid for the OKN dynamics in humans [2,7,8,10]. Therefore, in our present study we applied the correlation coefficient to test the relationships between the slow and fast phases of OKN signals in humans. Furthermore, we analyzed the variation in amplitudes from beat to beat in the sequence of running amplitudes. We tested

---

\*Corresponding author: Torbjørn Aasen, National Center for Vestibular Disorders, Department of Otorhinolaryngology/Head and Neck Surgery, Haukeland University Hospital, N-5021 Bergen, Norway. Tel.: +47 55 97 26 88; Fax: +47 55 97 26 43; E-mail: torbjorn@aaasens.net.

for short-term information patterns in the OKN amplitude time series signal by calculating the information entropy [11] of the probability distribution of words consisting of three symbols, which divides the OKN amplitude time series sequence into three equally numbered data sets.

## 2. Material and methods

### 2.1. Subject

Fourteen OKN signals were recorded in five healthy subjects with normal optokinetic nystagmus.

### 2.2. Recording technique

Horizontal eye movements were recorded with two electrodes, (Ag-AgCl skin electrodes), which were placed laterally to each eye, along with 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 a computer, using 12 bit A/D resolution and 100 Hz sampling frequency (sampling time  $\tau_s = 0.01$ ).

### 2.3. Optokinetic stimulation and registration

Optokinetic nystagmus was obtained by stimulating the visual field with  $3.75^\circ$  width vertical light stripes separated by  $11.25^\circ$  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 with their head restrained. They were instructed to not follow the stripes with the eyes, but to focus their vision on the screen, allowing the optokinetic reflex to control the eye-movements.

Seven recordings were performed with the movement of the stripes at a velocity of  $30^\circ/s$ , and seven recordings at  $60^\circ/s$ , both below and above the normal threshold for smooth pursuit function [6,9]. Each recording lasted for one minute.

### 2.4. Statistics

For the purpose of evaluating the relation between

the slow and fast phases, correlation coefficients between slow and subsequent fast phases ( $R_{sf}$ ), and fast and subsequent slow phases ( $R_{fs}$ ) were calculated. The Mann-Whitney U test was then applied to evaluate the differences between the means of the two groups of correlations.

For the purpose of testing for short-term information pattern in the optokinetic nystagmus amplitude time series signal, (a two second OKN time series is given in Fig. 1(a)), the following procedure was applied [1]: Find the OKN amplitude sequence,  $A_i$ , (Fig. 1(b)). Detect the two levels which divide the OKN amplitude sequence  $\{A_i\}_{i=1}^n$  into three equally numbered data sets (Fig. 1(c)). Transform  $A_i$  into the sequence of symbols  $s_i$  (Fig. 1(d)).

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

A one minute data series typically results in 350 symbols,  $s_i$  (which is doubled when using both the slow and fast phases).

Find the three-letter words series  $w_i$  (Fig. 1(e)).

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

Compute the probability density distribution,  $p_k$ , of the three-letter words series (Fig. 1(f)).

$$\left( \sum_{k=1}^{\#bins} p_k = 1, \right.$$

$$\left. \text{where } \#bins = \#symbols^{(\#word \text{ length})} = 27 \right)$$

Calculate the normalized information entropy,  $I$ , of the probability distribution

$$I = -\frac{1}{\text{Log}(27)} \sum_{k=1}^{27} p_k \text{Log}(p_k) \quad 0 \leq I \leq 1$$

For each sequence of symbols,  $s_i$ , 100 new series were generated by randomly changing the order of the sequence (the same symbols, but where the serial dependency is broken). The entropy parameter,  $I$ , of the three-letter words series probability distribution for the original sequence was then statistically tested against the distribution of the 100 interval shuffled  $I_{shuf}$  (null hypothesis  $H_0: I = \text{mean } I_{shuf}$ ) [7].

Due to the limited number of amplitudes in the OKN time series, reducing the number of possible outcomes from 4096 ( $2^{12}$ ) to 3 increases the possibility of detecting the dominant globally dynamic pattern in the data set.

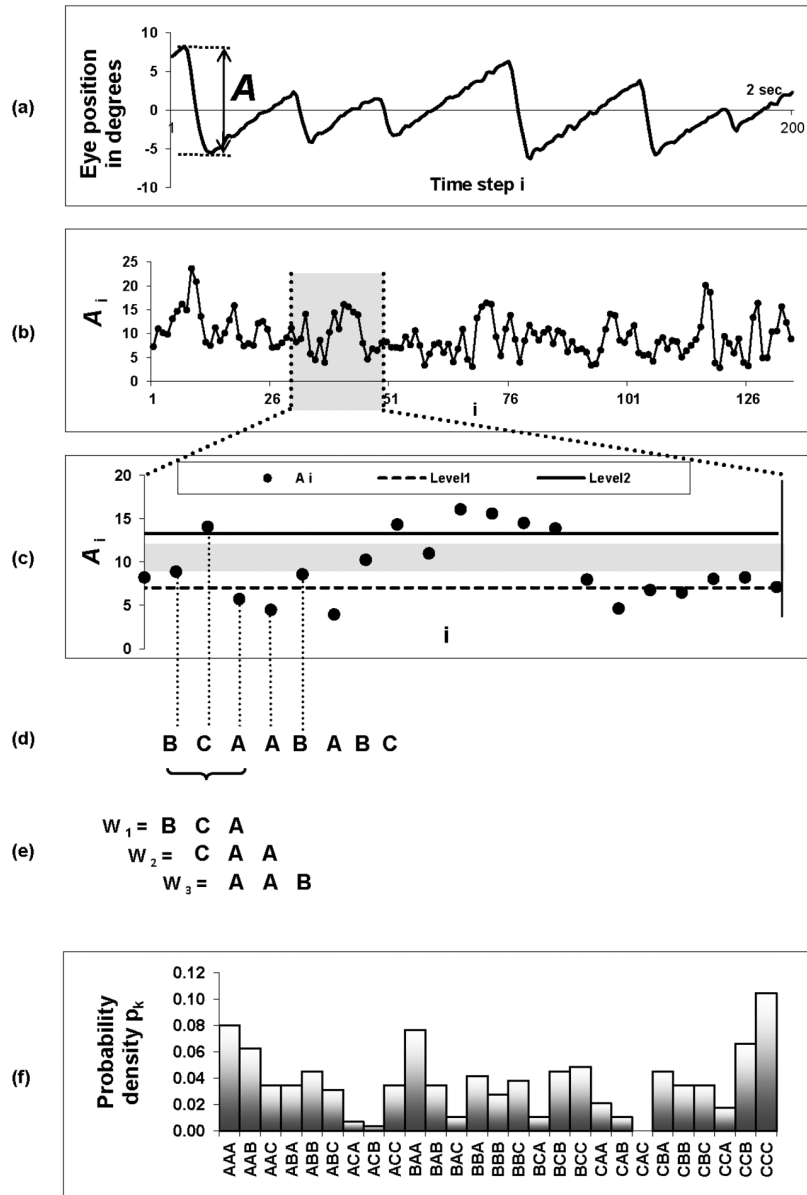


Fig. 1. (a) A two second registration of an optokinetic time series. Upward direction represents eye movement to the right, downward direction represents eye movement to the left. In (b) the OKN amplitude sequence is shown, (c) a segment of the OKN amplitude sequence, (d) the time series sequence of symbols, (e) the three-letter words series and (f) the probability density distribution of the three-letter words series.

### 3. Results

The mean correlation coefficient of OKN amplitudes ( $n = 14$ ) between slow and subsequent fast phases ( $R_{sf}$ ) was 0.54 (SD = 0.17), and between fast and subsequent slow phases ( $R_{fs}$ ) was 0.45 (SD = 0.16). No significant difference ( $p = 0.141$ ) was found between the two groups. No significant differences ( $p = 0.706$ ) were also found between the responses to

stimuli  $30^\circ/\text{sec}$  and  $60^\circ/\text{sec}$ , which represent velocities below and above the normal threshold for smooth pursuit function [6,9].

Figure 1(f) shows the probability distribution,  $p_k$ , of the three-letter words series,  $w_i$ . In our example some words occur more often than others, and a distinct pattern occur (because of equally numbered symbols,  $s_i$ , a random series would give equally numbered words,  $w_i$ , i.e., the distribution,  $p_k$ , will tend to be flat, and

Table 1

The entropy parameter,  $I$ , tested against 100 shuffled surrogates. The null hypothesis  $H_0: I = \text{mean } I_{\text{shuf}}$  is rejected when  $t > 2.626$ , which states that  $I$  is outside the 99% confidence interval of the shuffled distribution ( $p < 0.01$ ).  $t_A$  gives the  $t$  value for the entropy parameter,  $I$ , of the three-letter words probability distribution for the original sequence of subsequent OKN amplitudes (slow-fast-slow-fast, etc), statistically tested against the distribution of the 100 entropy parameters ( $I_{\text{shuf}}$ ) from the interval shuffled sequences, while  $t_{AS}$  gives the  $t$  value for the same statistic for the OKN slow amplitudes, and  $t_{AF}$  for the OKN fast amplitudes.

$t_A$	$t_{AS}$	$t_{AF}$
6.51*	0.35	1.95
7.41*	0.82	0.37
7.56*	0.77	0.96
8.43*	0.37	0.27
9.79*	2.54	0.83
9.92*	1.56	0.66
11.63*	1.36	1.12
13.74*	0.04	0.60
14.33*	0.71	1.52
15.35*	0.56	0.68
17.19*	1.52	0.25
17.41*	0.86	1.44
22.29*	3.88*	0.98
22.54*	5.52*	0.24

\* $t > 2.626$ ;  $I$  is outside the 99% confidence interval of the shuffled  $I_{\text{shuf}}$  distribution.

with infinitely many symbols it will be perfectly flat). Table 1 gives the  $t$ -values for the entropy parameter,  $I$ , tested against 100 shuffled surrogates,  $I_{\text{shuf}}$ . Each row in the table gives the  $t$ -values for one recording. We see that the entropy,  $I$ , of the original sequence of symbols is outside the 99% confidence interval ( $t > 2.626$ ) of the surrogates. When we tested the parameter  $I$  for the slow phases and the fast phases separately, we were only able to find information patterns for slow phase amplitude sequences for two of the 60°/sec stimulations.

#### 4. Discussion

In an earlier study, Chun and Robinson [3] presented a model simulating the observed slow and quick phases of nystagmus in cats. Data from the model showed a higher correlation between the slow and subsequent fast phases than the slow and previous fast phases of OKN amplitudes. In the study by Trillenberget al. [10], they refer to the findings of a high correlation between the slow phase and the following fast phase, previously reported by Chun and Robinson [3]. However, they did not find that the predictability of the fast phase beginning positions was higher than the predictability of the fast phase ending posi-

tions. This would have been expected if the correlation between the slow phases and following fast phases was higher than the correlation between the fast phases and following slow phases. Our study addresses the question of whether or not the slow phase amplitudes determine the fast phase amplitudes of OKN in humans. We found no differences between the correlation coefficient between slow and subsequent fast phases and fast and subsequent slow phases of OKN amplitudes. This is in agreement with the view that in order to function optimally, the saccadic catch up eye movement is not fully determined by the previous state [10]. One may speculate on whether a restraining of the freedom to rapidly focus on a new object might result in disturbed perception and dizziness, and may therefore be interpreted as a diagnostic sign.

Several diseases involve the vestibular and oculomotor systems and may lead to symptoms like vertigo and dizziness, to name a few. It is not always possible for the clinician to determine the cause of the symptoms from standard vestibular or ocular tests. The cause of the symptoms may not always be a locally discrete lesion, but a failure in the system organization, manifested in its functional dynamics. In order to diagnose such a condition, we need methods for analyzing variations in the system dynamics. In this study, we found a short-term information pattern in the OKN amplitude sequences. This is a precondition for developing diagnostic methods based on shifts in the dynamics of the OKN signal.

Electronystagmography is susceptible to baseline drift. If the absolute eye position is of importance, video-nystagmography or scleral search coils may be more appropriate methods. However, this study analyzed relative eye positions (nystagmus amplitudes), for which electronystagmography is a well-established method [4].

The mathematics applied in this study is easy to implement using a standard computer. The main challenge was to find an automatic robust algorithm to detect the start and end points of nystagmus. Our automatic algorithm rejected six out of twenty signals as a result of interrupted periods of suppressed nystagmus.

#### 5. Conclusion

Results from an earlier study suggested a high correlation between slow phase amplitudes and the following fast phase amplitudes and a lower correlation between fast phase amplitudes and the following slow

phase amplitudes in cats. Our study does not find the same correlation in humans. However, when we tested for serial dependence, we found OKN amplitude information patterns, which are somehow related to the neighboring slow fast and fast slow phases. This pattern was not part of the dynamics when separately testing for the slow phase and the fast phase amplitudes. The existence of serial dependence in OKN amplitude sequences reveals insight into physiological regulating mechanisms, and the application of information theoretical methods in the investigation of the vestibular and oculomotor systems.

### Acknowledgment

We thank Dr. Carla Olsnes for proofreading the article.

### References

- [1] T. Aasen, Symbolic dynamics applied to optokinetic nystagmus signals, *J Med Eng Techno* **27** (2003), 145–148.
- [2] T.J. Anastasio, A random walk model of fast-phase timing during optokinetic nystagmus, *Biol Cybern* **75** (1996), 1–9.
- [3] K.S. Chun and D.A. Robinson, A model of quick phase generation in the vestibuloocular reflex, *Biol Cybern* **28** (1978), 209–221.
- [4] L.F. Dell’Osso and R.B. Darof, Eye movement characteristics and recording techniques, in: *Neuro-ophthalmology*, (Third Edition), J.S. Glaser, ed., Lippincott Williams & Wilkins, Philadelphia, 1999, pp. 327–343.
- [5] M. Magnusson, L. Schalén, I. Pyykkö, H. Enbom and N.G. Henriksson, Clinical considerations concerning horizontal optokinetic nystagmus, *Acta Otolaryngol Suppl* **455** (1988), 53–57.
- [6] L. Schalén, Quantification of tracking eye movements in normal subjects, *Acta Otolaryngol* **90** (1980), 404–413.
- [7] M. Shelhamer, On the correlation dimension of optokinetic nystagmus eye movements: Computational parameters, filtering, nonstationarity, and surrogate data, *Biol Cybern* **76** (1997), 237–250.
- [8] M. Shelhamer, Nonlinear dynamic systems evaluation of ‘rhythmic’ eye movements (optokinetic nystagmus), *J Neurosci Methods* **83** (1998), 45–56.
- [9] D.J. Spalton, Neuro-Ophthalmology, in: *Slide atlas of ophthalmology*, D.J. Spalton, R.A. Hitchings and P.A. Hunter, eds, Gower Medical Publishing Ltd., 1984.
- [10] P. Trillenber, C. Gross and M. Shelhamer, Random walks, random sequences, and nonlinear dynamics in human optokinetic nystagmus, *J Appl Physiol* **91** (2001), 1750–1759.
- [11] A. Voss, J. Kurths, H.J. Kleiner, A. Wit, N. Wessel, P. Saparin, K.J. Osterziel, R. Schurath and R. Dietz, The application of methods of non-linear dynamics for the improved and predictive recognition of patients threatened by sudden cardiac death, *Cardiovasc Res* **31** (1996), 419–433.