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Automatic identification of eye movements using the largest lyapunov exponent

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ABSTRACT

The study of eye movements has been increasing over the past decade. It is considered that eye movements, mainly saccades and blinks, provide significant information for cognitive and visual processes of the observers. Saccades and blinks are high velocity eye movements. In this paper, the automatic identification of saccades and blinks, as well as their onset and offset, is proposed based on a novel implementation of nonlinear dynamics using the Largest Lyapunov Exponent and the logarithm of the divergence. The Largest Lyapunov Exponent detection method was tested on 25,000 saccades and 2,366 blinks, detecting with high accuracy and precision both types of eye movements. The Largest Lyapunov Exponent detection method was compared against two other existing techniques for blink and saccade identification, showing advantageous performance.

1. Introduction

Saccades are intended, rapid movements of eyes that bring the visual axis into a new position [1,2]. Their major applications include the study of normal vision as an indicator of human behaviour [3], as well as the differentiation of patients sufferring with various psychiatric disorders (for example schizophrenia or attention deficit) from normal controls [4]. Various methods have been proposed in the literature for the automated detection of saccades. Marple-Horvat et al. used the linked double window technique for the identification of saccades [5]. The onset and offset of saccades correspond to points of maximal eye velocity. These points were detected by scanning the velocity signal by two unequal windows that are linked and move together. The points in which the difference of the arithmetic mean of the signal values in the two windows is maximized were considered as the start/end of the saccades. The accuracy in identifying both vertical and horizontal saccades for each direction (left or right) was up to 95.0%. Salvucci and Goldberg compared various methods (Velocity Threshold, Dispersion Threshold, Hidden Markov Model, Minimum Spanning Tree and Area of Interest) for the identification of saccades during an equation solving experiment involving students [6]. According to the findings, the Velocity Threshold method encounters problems in noisy signals and when the velocity data points were aligned closely to the selected threshold. The Dispersion Threshold presented high complexity as it requires the estimation of two highly interdependent parameters. The Hidden Markov Model had the disadvantage of the re-estimation of observation and transition parameters. The Minimum Spanning Tree algorithm presented the weakness of not being a real-time application as all the fixation points are needed to form clusters. Finally, the Area of Interest algorithm suffered from the serious problem of including saccades into fixations. Based on these results, the number of the parameters required for the execution of each of the aforementioned algorithms, as well as the proper selection of them, are two crucial points for the correct identification of the saccades.

Nyström and Holmqvist proposed an algorithm for the detection of the onset and the offset of saccades making use of the velocity

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of eye movement [7]. Furthermore, the algorithm was also capable of identifying fixations and glissades. The specificity and sensitivity of the algorithm reached 96.0% and 90.0%, respectively. Besides eye velocity, the signal of eye acceleration has been involved in the detection of saccades, blinks, post-saccadic oscillations and fixations providing sensitivity between 66.7% and 97.8% and specificity between 82.8% and 99.9% [8]. Features from eye displacement and eye velocity signals (maximum value, mean value, standard deviation, kurtosis, skewness, energy and entropy) were combined for training and testing three Artificial Neural Networks in order to discriminate between saccades, micro-saccades, fixations and blinks [2]. The overall accuracy reached 95.9%.

Pettersson et al. proposed an algorithm for the accurate identification of blinks [9]. Firstly, the local maximal peaks of the absolute values of the signal were calculated. An amplitude difference between sorted consecutive peaks above 0.03 are characterized as blinks. The onset (offset) of the blink was identified as the 10% of the maximal amplitude, at left (right) of the peak. The algorithm tested in 213 blinks and achieved 93.0% detection sensitivity for blinks with 4% false positive rate.

Toivanen et al. presented a probabilistic algorithm for the identification of blinks and saccades, calculating the parameters of Gaussian likelihoods sample-by-sample, using an expectation maximization algorithm [10]. The algorithm was tested on EOG data recorded from 5 subjects during fixation tasks. The detection rates of the method in detecting blinks, saccades, and fixations were close to 100%. However, the performance of the algorithm depends on the saccadic angle and performs adequately for saccades above three degrees.

Many researchers have applied the Largest Lyapunov Exponent (LLE) for the identification and/or prediction of various diseases. The LLE describes the divergence/convergence of initially close trajectories with time. Jeong et al. proposed a nonlinear analysis of EEG in order to identify Alzheimer's disease patients. The arithmetic mean and the standard deviation of the LLE of the EEG signals from patients suffering from Alzheimer's disease were lower than those of normal controls [11]. Gulera et al. proposed the extraction of four statistical features of the Lyapunov exponents from EEG signals and fed into a Recurrent Neural Network, resulting in 96.1% accuracy of detecting epileptic seizure [12]. Goshvarpour et al. used the LLE for the detection of apnea during sleep from EEG signals. It was observed that the mean value of LLE was lower in apnea episodes than that of normal epochs [13]. Nonlinear techniques were also employed for the prediction of epilepsy in EEG signals [14]. According to this study, the analysis based on the LLEs was proved to be suitable to assess the non-deterministic behaviour of EEG signals. Specifically, it was estimated that the onset of the epilepsy can be identified using only the LLE from specified electrodes. It was observed that the LLE drops down approximately two minutes before the seizure onset, while at the onset of the epilepsy the lowest values of the LLE were presented. Consequently, seizure onset can be both detected and predicted.

The Lyapunov Exponent has been combined with other nonlinear characteristics, such as Correlation Dimension and Hurst Exponent, to improve the classification of biological signals (EEG and ECG data) [15]. Furthermore, the LLE provided accurate discrimination between the states of the sleep. Specifically, increased values in deep sleep were observed comparing to awake stage of sleep or light sleep. Also, in [16], the cortical function was described by employing nonlinear analysis of the EEG signal.

Although the Lyapunov exponents have been used in the past for the study of saccades [17], [18], the related papers mainly focused on the mechanism that produce saccades and did not offer a methodology to detect them. Specifically, in the study of Aştefănoaei et al., [17], eye movements were collected from healthy subjects by an infrared camera eye tracker, aiming to study the degree of complexity of the dynamics of the eye movement by means of the Hurst exponent and the LLE. The authors concluded that there is a high complexity dynamical trend of the eye movements in saccade tasks. The LLE suggested bi-stability of cellular membrane resting potential during saccadic experiment. Harezlak, [18], used the LLE for the identification of chaotic behaviour during fixation. Eye movements were recorded from 24 subjects into two sessions with two-month interval. Twenty nine stimuli were appeared on different points of the screen for 3 s. The subjects were asked to fixate to each point that appeared on the screen. The author concluded to a chaotic dynamic of eye movements for the first 200 points of the signal. Both previous studies consider the employment of the LLE for the recognition of stable states on the production of saccades and fixations.

The objective of this work is to present a new approach for the automatic identification of saccades and blinks using the LLE and the logarithm of the divergence. To the best of the authors' knowledge, it is the first time that the LLE and the logarithm of the divergence have been used to automatically identify saccades and blinks, as well as their onset and offset. The proposed method uses the raw signal exclusively, while most of the algorithms use the velocity and/or the acceleration signal as well. The innovation of the algorithm is the simultaneous identification of horizontal saccades and blinks with high accuracy, using a single sliding window, by means of the LLE. The proposed detection method does not require prior knowledge of the existence of the specific eye movements. Furthermore, it is applied on the original angular displacement signal, with no need to estimate velocity or acceleration signals.

The paper consists of three sections. In the first section, Materials and Methods, the data collection process and the proposed methodology are described. In the second section, the results of the identification of saccades and blinks by the LLE detection method are presented in comparison with other existing methods. Finally, in the last section, discussion of specific issues related to the selection of the values of the parameters that may influence the performance of the LLE detection method is presented along with future research directions.

2. Materials and methods

2.1. Data collection

The data set for this study is described in detail in a previous report [19]. In brief, 300 young men between 18 and 24 years old, serving in the Greek Air Force, participated in the study. The participants provided written informed consent. Each subject performed a series of oculomotor tasks (smooth eye-pursuit, saccade, antisaccade, active fixation). An infrared reflectometry (IRIS system, Scalar Ltd) recorded the (horizontal) eye movements of the right eye. The resolution of the recorded signals was 0.01°. The maximum saccadic angle was 20°. The signals were digitised by a 12-bit analog to digital converter (Advantech PC-lab Card 818L). The sampling rate of the converter was 600 samples/s.

Each individual participated into three different active visual fixation tasks. An active fixation task is defined as the ability to maintain fixation for a period of time [19]. The duration of each task was 50 s. The order of appearance of the tasks was random. The first task, called "visual fixation – undistracted" (VFU), required the participants to maintain their gaze on a visual target that appeared on the centre of a monitor. The target was a white cross with dimensions $0.3^\circ \times 0.3^\circ$ (Fig. 1a). The second task, called "visual fixation – distracted" (VFD), was similar to the first one, but with the presence of distracting targets to the right or the left of the central target. Two different kinds of distracting targets were used: a small white