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Automatic identification of oculomotor behavior using pattern recognition techniques

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ABSTRACT

In this paper, a methodological scheme for identifying distinct patterns of oculomotor behavior such as saccades, microsaccades, blinks and fixations from time series of eye's angular displacement is presented. The first step of the proposed methodology involves signal detrending for artifacts removal and estimation of eye's angular velocity. Then, feature vectors from fourteen first-order statistical features are formed from each angular displacement and velocity signal using sliding, fixed-length time windows. The obtained feature vectors are used for training and testing three artificial neural network classifiers, connected in cascade. The three classifiers discriminate between blinks and non-blinks, fixations and non-fixations and saccades and microsaccades, respectively. The proposed methodology was tested on a dataset from 1392 subjects, each performing three oculomotor fixation conditions.

The average overall accuracy of the three classifiers, with respect to the manual identification of eye movements by experts, was 95.9%. The proposed methodological scheme provided better results than the well-known Velocity Threshold algorithm, which was used for comparison. The findings of the present study indicate that the utilization of pattern recognition techniques in the task of identifying the various eye movements may provide accurate and robust results.

1. Introduction

Gesture, speech and eye movements are frequently analyzed by experts in order to explain human behavior. As a result, eye movements have enjoyed burgeoning attention in recent years as a tool for studying human behavior [1]. Perhaps the most important reason for their usefulness is that eye movements indicate the focus of visual attention although covert attention can be focused away from the point of visual fixation [2]. The eyes do not remain still when viewing a visual scene; they have to move constantly to build up a mental "map" from interesting parts of the scene [3]. The main reason for this is that only a small central region of the retina, the fovea, is able to perceive with high acuity.

According to Leigh and Zee [4], four basic types of eye movements can be identified: (1) Saccades, that are fast voluntary movements, which bring the fovea in the region of interest within the visual field, (2) smooth eye pursuit, that involves a slow continuous movement of both eyes in order to follow a moving visual stimulus in the visual field, (3) vergence, that is the disconjugate slow movements of the eyes that converge or diverge in order to foveate an object in three-dimensional space, and (4) fixation, that is the inhibition of all eye movements which keeps the eyes locked on a particular location in the orbit. When fixing the gaze, there exist microscopic and unnoticed motions of the eye, called fixational eye movements. Furthermore, saccades can be divided into two distinct groups: major saccades, that are easily observed even with naked eye and minor saccades that are virtually unobservable without special instrumentation [5]. The smallest saccades, called 'microsaccades', are involuntary eye movements produced during attempted visual fixation. They are the largest and fastest of the fixation eye movements [6].

Saccades have been extensively examined in normal vision towards the understanding of human behavior [7]. Apart from the study of normal vision, saccadic deviations have been also measured in special groups, such as patients with psychiatric disorders (such as attention deficit hyperactivity disorder (ADHD) and schizophrenia), young children and elderly people in an attempt to differentiate saccadic characteristics between those conditions and normal controls [8].

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Although eye movements have become increasingly popular as a tool for investigating behavior, the analysis of movements can be often extremely difficult and tedious [9]. A major objective for eye movement analysis could be the identification of the main eye movement types with no or minimal user intervention. Towards to this direction, eye movement characteristics have been analyzed in many studies and the visual behavior during specific tasks has been successfully modeled in an automatic manner. In [10], an analysis of eye movement using tracing methods in three conditions (equation solving, reading and gaze-based interfaces) from seven participants has been conducted. In order to identify fixation points and saccades, methods based on sequence-matching and Hidden Markov Models were used, resulting in identification of eye movements as accurately as human experts, but in significantly less time with an overall accuracy ranging between 87.5% and 93.7%. In another study, machine learning methods were used to improve the accuracy of detecting Mild Cognitive Impairment (MCI) in 60 participants, by modeling eye movement types such as fixations, saccades, and re-fixations during the Visual Paired Comparison task [11]. The features used were the fixation duration, re-fixations, saccade orientation and the pupil diameter which were fed as inputs to a Support Vector Machine (SVM) classifier. Using this classification algorithm, age-matched normal control subjects were distinguished from MCI subjects with an overall accuracy of 87.0%.

In a recent study, a set of 90 features, that describe the eye movement data, were collected from 10 participants under five activities: copying a text, reading a printed paper, taking handwritten notes, watching a video, and browsing the web [12]. The features included, among other, the mean and the variance of the saccade signal amplitude, the maximum electro-oculographic (EOG) signal amplitudes, the rate of small or large saccades, and the positive and the negative saccades in horizontal or vertical direction. These features were ranked and evaluated using the minimum redundancy maximum relevance feature selection method along with an SVM classifier in order to automatically discriminate these five activities resulting in 80.2% overall accuracy. In [13] a new velocity-based algorithm that makes the saccade detection less sensitive to variations in noise level was suggested. The algorithm includes a data driven threshold for peak and saccade onset/offset detection, an adaptive threshold adjustment based on local noise levels, physical constraints on eye-movements to exclude noise and new recommendations for minimum allowed fixation and saccade duration. The algorithm detects saccades and postsaccadic oscillations in the presence of smooth pursuit movements with 92.0–96.0% specificity and 80.0–90.0% sensitivity. In another study, a method for the detection of saccades, blinks, postsaccadic oscillations and fixations in the acceleration domain was presented [14]. The method was a two-step procedure that involved the identification of approximate saccadic intervals and saccadic onset and offset detection. The method was applied on eye-tracking signals from 33 subjects that performed three different tasks and provided sensitivity between 66.7% and 97.8% and specificity between 82.8% and 99.9%. In another study, the development of robust and accurate microsaccade detection techniques was presented, based on unsupervised clustering techniques [15]. The new clustering method validated using an eye-movement database included recordings from 20 adult subjects (12 men, 8 women) with normal or corrected-to normal vision that maintained fixation on a centrally presented target, and simulated eye-movement data. The clustering method compared other microsaccade-detection techniques conclude to higher performance both for binocular and monocular data. The median error rate in the method proposed in [16] was 0.25 errors per second, while the median error rate in the clustering method was 0.1 errors per second. The sensitivity of detecting microsaccades for both methods is more than 75%, using manual labeling as the gold standard. Also, in [17], participants were asked to fixate a small dot on a computer display and microsaccades were detected in two dimensional velocity space by using thresholds for peak velocity and a minimum duration, implemented as an improved version of an algorithm proposed earlier [16].

The purpose of the proposed study was to develop a methodology for the automatic classification of eye movements of healthy individuals into four categories: saccades, microsaccades, blinks and fixation. Towards this direction, 2335 oculomotor signals from 1392 individuals have been processed, in order to automatically identify specific characteristics of the saccadic eye movements [18]. The proposed methodology involves an array of three neural network classifiers: the first classifier discriminate blinks from non-blinks, the second one separates fixation from all types of saccades and finally the third one which differentiates microsaccades from major saccades. To our knowledge, it is the first attempt towards the automatic identification of different types of eye movement characteristics, including saccades and microsaccades, from a very large database of oculomotor signals.

2. Materials and methods

2.1. Data acquisition

This study used the oculomotor dataset from the ASPIS sample (Athens Study for Psychosis Proneness and Incidence of Schizophrenia) according to Smyrnis et al. and Evdokimidis et al. [18,19]. A sample of 1778 young male subjects aged 18–24 years were recruited from the Greek Air Force. These agreed to participate in the study after giving written informed consent. These individuals performed a battery of eye movement tasks (smooth eye pursuit, saccade, antisaccade, visual fixation) and cognitive tasks and they also completed questionnaires for a detailed psychometric analysis. Each subject from the ASPIS sample has been codified with a unique number code. The correlation between the subjects and the codes has been destroyed. The subject's horizontal eye movements (angular displacement) were recorded from the right eye only using the IRIS SCALAR infrared device (spatial resolution: 2 min of arc) [19]. A chin rest was used to stabilize the head. A 12-bit A/D converter was used for data acquisition (Advantech PC-lab Card 818L). The data were sampled at 600 Hz, providing 30,000 samples for time duration of 50 s.

The participants performed three fixation conditions [19]. In the first fixation condition, the participants were instructed to simply fixate a visual target on the center of the computer monitor (white cross $0.3^\circ \times 0.3^\circ$) for 50 s. In the second fixation condition, the participants were asked to fixate again a central target and ignore targets that might appear to the right or the left. For each trial four distracting targets were used; two small, $0.3^\circ \times 0.3^\circ$ white crosses and two large, $0.1^\circ \times 0.1^\circ$ crosses, each presented for 500 ms at random intervals during the 50-s fixation period. The distracting targets could appear at a random distance of $2^\circ - 9^\circ$ and a random direction at left or at right from the center. Finally, in the third fixation condition, the participants were asked to keep their eyes fixating in the primary position (straight ahead) in front of a black screen and avoid making eye movements.

Before each active fixation condition, a calibration procedure was performed that consisted of saccadic movements at targets located 10° to the right and left of a central fixation target (see Fig. 1a). In some cases, due to the motion of the individual and/or the instability of the device that was placed on the participant's head, the calibration signal was corrupted by noise (see Fig. 1b). The signals from these participants were excluded from the study. Furthermore, there were cases that the calibration signals were not corrupted by noise but the recorded signals presented a strong noise component (Fig. 1c). These noisy signals were smoothed using a bandpass filter as it is presented in Fig. 1d.

A total set of 2335 oculomotor signals from 1392 individuals were finally selected for further analysis. Two experts of Eginition Hospital in Athens (Smyrnis and Evdokimidis) identified the types