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Detection of fixations and smooth pursuit movements in high-speed eye-tracking data

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ABSTRACT

A novel algorithm for the detection of fixations and smooth pursuit movements in high-speed eye-tracking data is proposed, which uses a three-stage procedure to divide the intersaccadic intervals into a sequence of fixation and smooth pursuit events. The first stage performs a preliminary segmentation while the latter two stages evaluate the characteristics of each such segment and reorganize the preliminary segments into fixations and smooth pursuit events. Five different performance measures are calculated to investigate different aspects of the algorithm's behavior. The algorithm is compared to the current state-of-the-art (I-VDT and the algorithm in [11]), as well as to annotations by two experts. The proposed algorithm performs considerably better (average Cohen's kappa 0.42) than the I-VDT algorithm (average Cohen's kappa 0.20) and the algorithm in [11] (average Cohen's kappa 0.16), when compared to the experts' annotations.

1. Introduction

Measurement of eye movements is an important tool in basic research in, e.g., visual attention, perception, cognition, and medicine. In studies of visual attention and perception, eye movements are used to investigate, e.g., how the focus of our attention is chosen depending on the content of an image [1], how objects are identified [2], and how decisions are made [3]. In medicine, eye tracking is employed in studies investigating the functionality of the brain, e.g., in patients with schizophrenia [4].

Until recently, the majority of eye-tracking studies have used static stimuli, e.g., images and texts. The two most common types of eye movements when viewing static stimuli are *fixations* and *saccades*. Fixations are periods when the eye is more or less still, while saccades are fast movements between the fixations that take the eyes from one object of interest to the next. Currently, the interest in dynamic stimuli is growing and it is becoming increasingly common to conduct studies where video clips are used as stimuli [5]. The type of eye movement called *smoothpursuit* occurs when the eyes are following a moving object [6]. Traditionally, algorithms have been developed for signals recorded during static stimuli, i.e., developed to detect fixations and saccades. When smooth pursuit movements are not considered by an algorithm, they will be spread into the other types of detected eye movements and make the interpretation of these difficult. Smooth pursuit movements may for instance be erroneously classified as very long fixations interspersed with very short saccades [7].

Many of the measures that earlier have been used to investigate eye movements during image viewing are based on the detection of fixations and their properties, e.g., fixation duration and number of fixations [8]. When dynamic stimuli are used, these fixation measures are still of interest. However, in order to be able to investigate and draw well-founded conclusions from fixations in data where smooth pursuit movements are present, a robust algorithm for separation of fixations and smooth pursuit movements is needed.

Since the signal characteristics of fixations and smooth pursuit movements are overlapping [9], classification of fixations in the presence of smooth pursuit movements is a difficult task [5,10]. The task is also different depending on whether the algorithm is intended for analysis of data recorded with a high or low sampling frequency, and for real-time or offline processing. Classification of data with different sampling frequencies require different event detection methods, mainly due to differences in the level of high frequency noise.

In [10], three algorithms for detection of fixations, saccades, and smooth pursuit movements were evaluated: a velocity based algorithm with two velocity thresholds (I-VVT), a velocity and

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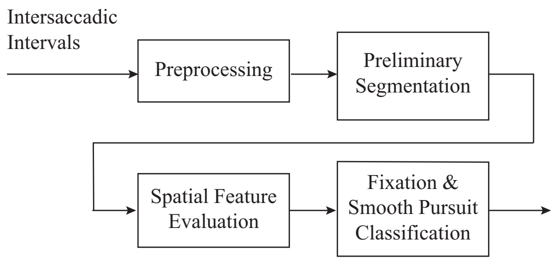

Fig. 1. Overview of the proposed algorithm.

movement pattern based algorithm (I-VMP), and a velocity and dispersion based algorithm (I-VDT). All algorithms were evaluated with data recorded using the EyeLink 1000 from SR Research. The stimuli consisted of dots moving with different speeds and different directions. The results showed that the most successful method was the I-VDT, which used a combination of velocity and dispersion thresholds.

Another algorithm, proposed in [11], employed principal component analysis in combination with a velocity threshold to distinguish between saccades, fixations, and smooth pursuit movements. The algorithm was used to analyze saccades in humans and monkeys watching short video clips, but the performance of the algorithm was not evaluated in detail. In the following, the algorithm proposed in [11] is referred to as I-PCA.

A completely different method, intended for real-time detection of smooth pursuit movements using a low-speed mobile eye-tracker was proposed in [12]. The method used a set of features and a k-nearest neighbor classifier in order to distinguish between smooth pursuit movements and the remaining parts of the data. The performance of the algorithm was evaluated using data recorded with stimuli where a dot was moving over the screen in different speeds and different directions. The results showed that a combination of features that capture temporal aspects of smooth pursuit movements was a successful detection method.

In this work, the focus is on offline processing of fixations and smooth pursuit movements in data recorded using a high-speed eye-tracker. The paper consists of two main parts: Firstly, an algorithm for classification of fixations and smooth pursuit movements is developed for eye-tracking data when dynamic stimuli are used, and secondly, a detailed evaluation is performed, where the performance of the algorithm is evaluated from different aspects.

2. Methods

A schematic overview of the proposed algorithm for detection of fixations and smooth pursuit movements is shown in Fig. 1. The algorithm is applied to the *intersaccadic intervals*, i.e., the intervals between the detected saccades, PSO, and blinks, and comprises three stages where the first stage performs a preliminary segmentation while the latter two evaluate the characteristics of each such segment and reorganize the preliminary segments into fixations and smooth pursuit events. In this paper, the intersaccadic intervals are identified using the algorithm in [13].

2.1. Preprocessing

In order to avoid any influence of adjacent saccades or PSO, the intersaccadic intervals are preprocessed. Since neither fixations nor smooth pursuit movements physiologically can have a velocity higher than 100°/s [14], the sample-to-sample velocities of the intervals are computed and all samples in the beginning and/or end of each interval exceeding this threshold are removed.

2.2. Preliminary segmentation

Each intersaccadic interval is divided into windows, w_i, of size t_w (ms), with an overlap of t_o (ms). For all pairs of x- and y-coordinates contained in the window, the sample-to-sample direction, $\alpha(n)$, is computed as the angle of the line between two consecutive pairs of x- and y-coordinates to the x-axis. In order to investigate whether the sample-to-sample directions in each window are consistent a Rayleigh test is performed [15]. The sample-to-sample direction, $\alpha(n)$, is transformed into Cartesian coordinates $r_i(n)$, for $n = 1, 2, \ldots, N-1$, where N is the number of samples in w_i.

$$r_i(n) = \begin{pmatrix} \sin(\alpha(n)) \\ \cos(\alpha(n)) \end{pmatrix} \tag{1}$$

The mean vector, $\bar{r}_i$, is calculated as

$$\bar{r}_i = \frac{1}{N}\sum_{n=1}^{N} r_i(n) \tag{2}$$

The Reyleigh test uses the resultant vector $R_i = \| \bar{r}_i \|$ to determine whether the sample-to-sample directions in the window are uniformly distributed or not. An approximation of the p-value under H_0 is computed using

$$P_i = \exp[\sqrt{1 + 4N + 4(N^2 - (R_i \cdot N)^2)} - (1 + 2N)] \tag{3}$$

The null and alternative hypotheses of the test, H_0 and H_A, respectively, are:

- H_0: The samples in the window are distributed uniformly around the unit circle.
- H_A: The samples in the window are not distributed uniformly around the unit circle.

The p-value of the test, P_i, is computed for each window i. Since there is an overlap between the windows, each sample may belong to more than one window. The mean value of P_j, for all windows j which sample k belongs to is computed as,

$$P_{\text{mean}}(k) = \frac{1}{K}\sum_{j=1}^{K} P_j \tag{4}$$

where K is the number of windows each sample belongs to, $k = 1, 2, \ldots, M$, and M is the number of samples in the intersaccadic interval. All consecutive samples in the interval satisfying either $P_{\text{mean}}(k) \geq \eta_P$ or $P_{\text{mean}}(k) < \eta_P$ are grouped together into preliminary segments sharing similar properties in terms of directionality. These preliminary segments are further analyzed in the next step.

2.3. Evaluation of spatial features in the position signal

For all preliminary segments that have a duration longer than $t_{\min}$, four parameters, p_D, p_{CD}, p_{PD}, and p_R, are calculated. These four parameters describe the dispersion (D), the consistency in the direction (CD), the positional displacement (PD), and the range (R) of the segment, which all are parameters that are typical for a smooth pursuit movement. In order to measure the dispersion, Principle Component Analysis (PCA) is employed. The first principle component determines the direction in which the data have their largest variance and the second principle component is chosen orthogonal to the first one. The principle components, pc_1 and pc_2, are computed by removing the respective mean from the preliminary x- and y-segments and estimating the covariance matrix, $\hat{C}$, between these. The zero mean data are projected onto the principle components, d_{pc_1} and d_{pc_2} respectively, and the lengths of the