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Microsaccade detection using pupil and corneal reflection signals

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ABSTRACT

In contemporary research, microsaccade detection is typically performed using the calibrated gaze-velocity signal acquired from a video-based eye tracker. To generate this signal, the pupil and corneal reflection (CR) signals are subtracted from each other and a differentiation filter is applied, both of which may prevent small microsaccades from being detected due to signal distortion and noise amplification. We propose a new algorithm where microsaccades are detected directly from uncalibrated pupil-, and CR signals. It is based on detrending followed by windowed correlation between pupil and CR signals. The proposed algorithm outperforms the most commonly used algorithm in the field (Engbert & Kliegl, 2003), in particular for small amplitude microsaccades that are difficult to see in the velocity signal even with the naked eye. We argue that it is advantageous to consider the most basic output of the eye tracker, i.e. pupil-, and CR signals, when detecting small microsaccades.

KEYWORDS

Eye tracking, microsaccades, event detection

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1 INTRODUCTION

The eyes are not completely still even when participants are asked to fixate a small target. Instead, three types of eye movements occur: rapid microsaccades, slow drift, and low-amplitude, high frequency tremor [Martinez-Conde et al. 2004; Poletti and Rucci 2016; Rolfs 2009]. Most attention has been given to microsaccades which share many of the dynamic properties with larger, voluntary saccades, and are typically described to occur 1-2 times per second and with amplitudes less than one degree (but different opinions exist, see e.g., [Nyström et al. 2014]). Recently, there has been an increased interest in investigating microsaccades, for instance since they have shown to be sensitive to transients in visual input, changes in cognitive state, and anticipation [Fried et al. 2014; Scholes et al. 2015; Siegenthaler et al. 2014].

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A crucial part of investigating microsaccades in basic and clinical research is to be able to accurately detect them in the eye-tracker signal as well as calculating appropriate statistics such as the rate, amplitude, and peak velocity. In the early days of research, this was typically done by manual inspection of photographic records of the recordings [Nachmias 1959]. Today, a couple of computer algorithms have become standard tools to separate microsaccades from other parts of the gaze signal [Engbert and Kliegl 2003b; Engbert and Mergenthaler 2006; Otero-Millan et al. 2014].

In the most widely used algorithm by Engbert and Kliegl [2003b] (EK), microsaccades are detected as outliers in a 2D velocity space if more than N samples exceed a velocity threshold $\eta_{x,y} = \lambda_{x,y} \sigma_{x,y}$, where

$$\sigma_{x,y} = \langle v_{x,y}^2 \rangle - \langle v_{x,y} \rangle^2 \quad (1)$$

and λ is a constant typically set to $\lambda = 6$. $\langle \rangle$ denotes the median estimator. The velocity v is computed directly from the (x, y) gaze coordinates using a moving average filter

$$\vec{v}_n = \frac{\vec{x}_{n+2} + \vec{x}_{n+1} - \vec{x}_{n-1} - \vec{x}_{n-2}}{6\Delta t} \quad (2)$$

A more recent algorithm uses the same principle to detect microsaccade candidates by finding local peaks in the velocity signal [Otero-Millan et al. 2014]. The number of microsaccade candidates are however upper bounded by the assumption that the maximum possible rate is five candidates per second. Since the average rate is typically lower, this means that some of the microsaccade candidates likely represent noise. Therefore, this algorithm applies k -means clustering based on velocity and acceleration features to separate microsaccades from noise.

Despite the improvements on the algorithmic side of microsaccade detection, a more fundamental problem is that even the most precise video-based eye tracker may have too low signal-to-noise ratios to reliably detect the smallest microsaccades, in particular when compared to older attachment devices [Collewijn and Kowler 2008]. As an example, several reports of monocular microsaccades can be found in the literature [Engbert and Kliegl 2003a; Gautier et al. 2016], even though their existence rather is a result of failing to detect a microsaccade in one eye (false negative) or detecting a microsaccade due to noise (false positive) [Nyström et al. 2017].

Part of the reason for errors in microsaccade detection is related to signal processing inherent to the eye tracker and microsaccade detection algorithms. Sources of noise and signal distortion in the gaze- and velocity-signals include subtracting the pupil and CR signals [Hooge et al. 2016], mapping of pupil and CR signals to a gaze signal (i.e., the calibration), and differentiation of the gaze signal to compute velocity. Such signal processing may hide or distort

genuine microsaccades and create microsaccade-like segments in the signal even though no oculomotor microsaccade took place.

In the paper, we propose a new and fundamentally different microsaccade detection algorithm using ‘raw’ and uncalibrated pupil and CR signals acquired binocularly with an EyeLink 1000 Plus. The algorithm avoids all of the sources of noise and distortion above since it uses signals that directly reflect how tracked eye features move in the camera image. It uses the fact that during a microsaccade, the positions of the pupil and the CR in the camera image are highly correlated and move faster than positional changes due to small head movement or drift. The algorithm specifically targets small microsaccades that may be hard to even see in the gaze signal, but are clearly visible in the pupil and CR signals [Nyström et al. 2017].

The proposed algorithm will be compared to manual annotations and with the most widely used algorithm in the literature [Engbert and Kliegl 2003b], both in terms of overall statistics and with a few examples highlighting the increased sensitivity of our proposed method.

2 DESCRIPTION OF NEW ALGORITHM

The new algorithm, henceforth denoted NN, operates directly on the pupil-, and CR signals obtained from the eye tracker. These signals are given in pixels in the coordinate system of the eye tracker’s camera.

The pupil-, and CR signals (Figure 1, top panel) for each eye are first ‘detrended’ (Fig 1, middle panel) such that slow variation in the signals is removed while fast variation, i.e., the microsaccades, are retained. Detrending is performed by subtracting each signal with a lowpass filtered version of the corresponding original signal. The lowpass filter in this work is a third order Savitzky-Golay filter of length L_{sg} [Savitzky and Golay 1964].

The detrending should ideally remove all slow variation in the pupil-, and CR signals due to e.g., small head movements, drift, or pupil dilation. As a result, the correlation between the detrended pupil-, and CR signals is effectively reduced in the intra microsaccadic intervals (IMSI). Figure 1 (bottom panel) shows the result of computing this correlation within a moving window of length L_c . As expected, the correlation is close to zero in the IMSIs, and peaks when a microsaccade occurs. Microsaccade candidates are detected when the correlation exceeds a threshold η' which, analogous to the work in [Engbert and Kliegl 2003b], is computed as a multiple of the variation σ' in the correlation signal $\eta' = \lambda' \sigma'$. Only microsaccade candidates spanning at least δ samples of are accepted as microsaccades. If two microsaccade candidates are closer than γ samples apart, they are merged into one.

The NN algorithm above is described for pupil-, and CR signals from one eye. If binocular data are available, there are two possible options. First, average the correlation signals before applying the algorithm and, second, detect the microsaccades monocularly, and identify binocular microsaccade using an overlap criterion [Engbert and Mergenthaler 2006]. In this paper the latter option is used.

3 EVALUATION

The NN and EK algorithms are evaluated on data from four participants recorded with an EyeLink 1000 Plus. In brief, binocular

Table 1: Microsaccade rate and amplitude (M and SD) for each participant (PID) and algorithm (Algo). Amplitudes are given in degrees. HC means human coder.

PID	Algo	N	Rate	Amp (M)	Amp (SD)
1	EK	292	1.44	0.09	0.04
	NN	301	1.49	0.11	0.04
	HC	292	1.44	0.10	0.06
2	EK	438	2.10	0.50	0.35
	NN	397	1.90	0.33	0.23
	HC	474	2.27	0.37	0.31
3	EK	240	1.17	0.17	0.09
	NN	259	1.26	0.16	0.07
	HC	260	1.26	0.15	0.08
4	EK	112	0.56	0.31	0.17
	NN	115	0.57	0.26	0.16
	HC	113	0.56	0.27	0.16

pupil-, and CR data were collected at 1000 Hz while participants fixated a small target in the center of a screen. Details about the recordings and data are provided in [Nyström et al. 2017].

The results below are generated with the parameters $\{\lambda' = 25, L_c = 13, \delta = 3, \gamma = 10, L_{sg} = 61\}$. The EK algorithm was used as described in [Nyström et al. 2017].

Detections from the algorithms were also compared with annotation from a human coder (one of the authors).

In Table 1, microsaccade rate and amplitudes are presented for both algorithms. Again, there is a high agreement in rate and amplitudes between the algorithms where the NN-algorithm finds slightly more microsaccades for three of the participants (P1, P3, P4). To opposite is however true for participant P2.

To quantify the overall agreement between the two algorithms and the human coder (HC), the F_1 -score is used. In case two microsaccades detected with one algorithm overlap with the same microsaccade detected with the other algorithm, only one of them is consider a match [Hooge et al. 2017]. A score of 1 means perfect agreement whereas 0 is the worst possible score. Figure 2 shows the agreement between the two algorithms and the human coder. Overall, the agreement is high, which means that both algorithms agree with each other and the human coder on where the microsaccades are located. For three of the participants (P1, P3, and P4), the agreement between the human coder and the NN-algorithm is higher than the agreement between the human coder and the EK-algorithm. It is also interesting to note that in the same three participants, the algorithms agree more with each other than the human coder agrees with the EK-algorithm.

To probe the nature of the differences across algorithms and participants, two examples are presented. Figure 3 illustrates why a larger number of microsaccades are detected by the EK algorithm than the NN algorithm for P2. As can be seen from the figure, this participant produces many square wave jerks (SWJ), and the NN-algorithm cannot separate the pair of microsaccades due to their close temporal proximity and because it is more difficult to precisely

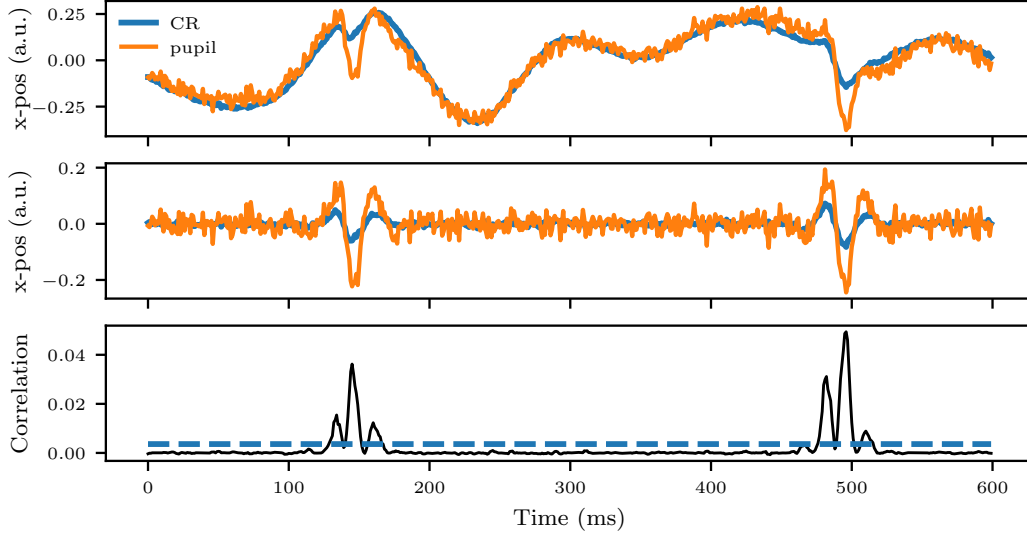


Figure 1: Raw pupil-, and CR data (top panel), Detrended pupil-, and CR data (middle panel), and moving window correlation between detrended pupil-, and CR data (bottom panel). The dashed line indicate the threshold used to detect microsaccades. Data represent horizontal movements of one eye relative to the eye-tracker’s camera.

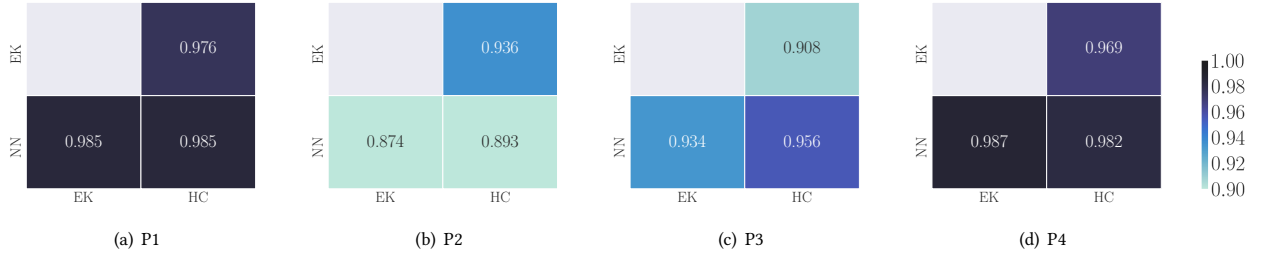


Figure 2: F_1 -scores between the two algorithms (NN and EK) and the human coder (HC) for each participant (P).

determine the exact onset and offset of the microsaccade in the correlation signal compared to the velocity signal.

A larger number of microsaccades are reported by the NN-algorithm for the remaining participants (P1, P3, P4). Figure 4 provides insight into the origin of these additional detections. As can be seen, small microsaccades are more easily detected in the correlation signal compared to the velocity signal, where small eye movements are obscured by noise.

4 DISCUSSION

A new algorithm for microsaccade detection was proposed. Unlike traditional methods using the calibrated gaze signal, we use the raw pupil-, and corneal reflection (CR) signal directly as the microsaccades may be detected more easily and reliably [Nyström et al. 2017].

The proposed NN-algorithm showed a similar performance with manual annotation from a human coder and to the most widely

used algorithm in the field [Engbert and Kliegl 2003b; Engbert and Mergenthaler 2006], but with a potential improvement in sensitivity to detect small microsaccades. This is a welcome contribution since the detection of low amplitude microsaccades in data from video-based eye tracker is controversial [Collewijn and Kowler 2008; Poletti and Rucci 2016], and has led to research findings that were later challenged [Gautier et al. 2016; Nyström et al. 2017].

There is room for future improvements of the NN-algorithm. Since it uses the moving window correlation between pupil- and CR signals, it is difficult to find the exact onset and offset of a microsaccade, since the correlation typically increases/decreases slightly before/after the actual eye movement. This is problematic for two reasons. First, to get accurate estimates of the amplitude it is critical to know when a microsaccade start and stops. Second, microsaccades that occur within a short temporal interval, for instance due to SWJ, may be difficult to separate, and are merged into one longer microsaccade.

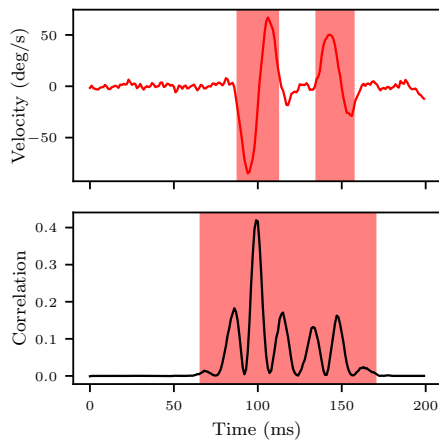


Figure 3: Detection of a square wave jerk (SWJ) using the velocity signal in EK (upper panel) and the correlation signal in NN (lower panel). Microsaccades with a small temporal separation often become merged with NN. Shaded regions indicate detected microsaccades. Data represent horizontal movements of one eye relative to the eye-tracker’s camera.

Ongoing work intended for a longer journal article includes finding solutions to these issues as well as a more thorough comparison including other algorithms as well as more hand coded data, still considered the ‘gold standard’ in the field.

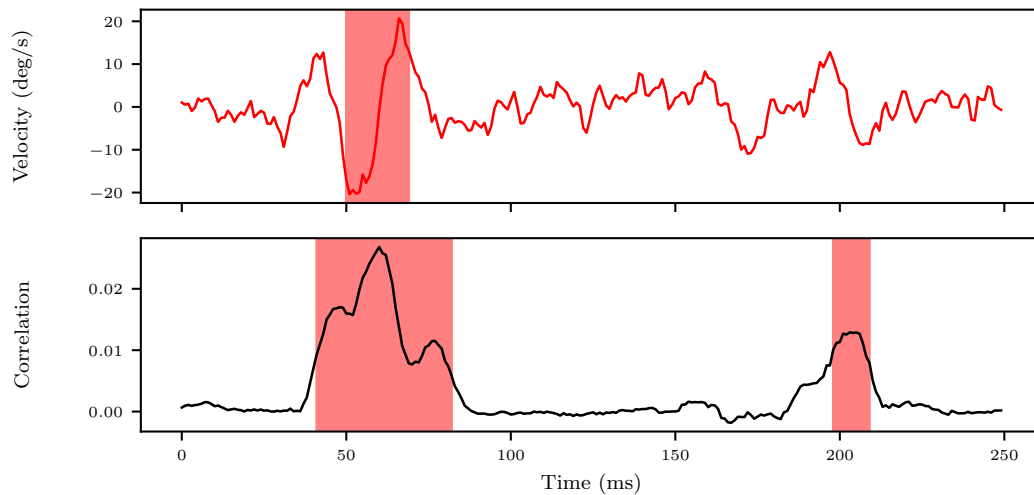


Figure 4: The velocity signal in EK (upper panel) and the correlation signal in NN (lower panel) over a 250 ms time window. Two microsaccades are detected by the NN algorithm. However, the smaller microsaccade is not picked up by the EK algorithm. Shaded regions indicate detected microsaccades. Data represent horizontal movements of one eye relative to the eye-tracker’s camera.

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