Stuart S, Galna B, Lord S, Rochester L, Godfrey A. Quantifying saccades while walking: Validity of a novel velocity-based algorithm for mobile eye tracking. *In: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2014, Chicago, Illinois: IEEE.

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DOI link to article:

http://dx.doi.org/10.1109/EMBC.2014.6944931

Date deposited:

18/01/2016

Newcastle University ePrints - eprint.ncl.ac.uk

Quantifying saccades while walking: validity of a novel velocity-based algorithm for mobile eye tracking

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***Abstract*— We validate a novel algorithm to detect saccades from raw data obtained during walking from a mobile infra-red eye-tracking device. The algorithm was based on a velocity threshold detection method, which excluded artefacts such as blinks and flickers using specific criteria. Mobile infra-red eye-tracking was performed with a group of healthy older adults (n=5) and Parkinson's disease (n=5) subjects. Saccades determined from raw eye tracker data obtained during walking using the algorithm were compared to a ground truth dataset defined as frame-by-frame visual inspection of raw eye-tracking videos. 100 trials from 10 subjects were analyzed and compared. The algorithm was highly reliable when compared to the ground truth (ICC(2,1) = 0.94), with an overall correct saccade detection percentage of 85%. This provides a simple yet robust algorithm for the analysis of mobile eye-tracking data.**

I. Introduction

Eye-tracking has been used since the 1700's. [1] It is becoming a very useful tool in the development of protocols that investigate cognitive and visual processes, as eye movement research has shown insight about underlying cognitive processes [2]. Recently the move from static to mobile eye-trackers has opened up possibilities to explore eye movements during dynamic activities, such as walking [3, 4], driving [5, 6], obstacle crossing [7], and stepping [8]. In these situations and other tasks, research is often concentrated on the analysis of saccadic eye movement (fast eye movement between fixation points) and fixations (pauses on areas of interest). Common visual outcomes include fixation durations, saccade frequencies, durations, velocities, amplitudes, and various other parameters.

In order to provide saccade and fixation data from the raw co-ordinate data acquired by mobile eye-tracking devices an algorithm is required. There are several different methods to extract this data (for an overview see; [9]). Velocity based saccade and fixation identification is the simplest method to understand and implement in eye tracking data analysis. This method consists of separating fixations and saccades based on their point to point (co-ordinate) velocities. Typically, fixations are classified as low velocities (i.e. <100°/sec) and saccades as high velocities (i.e. >300°/sec) [9]. Due to the velocity differences the discrimination of saccadic eye movements and fixations is relatively simple and robust. In view of this researchers have called for a readily adaptable algorithm for velocity based eye movement detection [10], which is particularly relevant when eye tracking in mobile environments where other eye movements (i.e. vestibular-occular reflex (VOR)), could infiltrate the thresholds [11].

The aim of this study was to provide a simple, yet robust algorithm for the detection of saccades from mobile eye-tracker data from which other metrics could be reliably determined. The work involves the development and initial validation of an algorithm to detect basic visual events (saccades) and associated outcomes (fixations) from mobile eye-tracker co-ordinate data.

II. Background

A. Mobile eye-tracking

The eye has a distinct black circle in its centre called the pupil, which is used as a frame of reference by eye-tracking technology to denote movement of the eye [11, 13]. Some but not all eye trackers also track the reflection of the cornea [13], which can be used to monitor camera position in relation to head movement.

B. Focus

Most medically orientated studies involving the analysis of eye movement characteristics aim to uncover the impairments of certain disease groups, such as people with Parkinson's disease (PD) during certain tasks. However, until recently almost all previous research was conducted in restricted static conditions and involved simple tasks such as button pressing [12]. These studies provide information about the mechanisms behind eye movement characteristics and allow for experimental manipulation, but results may not be relevant to real-world activities that involve multiple motor, cognitive and visual processes. Static conditions also limit the amount of error seen within eye-tracking data, as other artefacts associated with movement are not present (i.e. VOR). These artefacts must either be ruled out or controlled for when analysing for specific eye movement characteristics during real-world (highly mobile) activities.

III. Methods

A. Participants

Data were collected during an ongoing study 'Visual Function during Gait in Parkinson's disease (PD)' at Newcastle University and had ethical approval (Newcastle and North Tyneside 1 REC; REF: 13/NE/0128). Written informed consent was gained from each participant. This study involves the recording of eye-movements made while walking under different conditions (such as with a door frame, while turning, under dual task) in people with PD and healthy older adult controls. Ten participants were used to evaluate the algorithm. Five participants with PD and five healthy controls (HC) (>50 years old) were chosen at random from the larger study cohort.

B. Equipment

A Dikablis mobile eye-tracker (Erogneers, Germany) was used to track the participants' gaze co-ordinates (x, y) by means of infra-red illumination. This allows for the detection of the blackness of the pupil. The Dikablis was head-mounted on each participant

Research supported by supported by the National Institute for Health Research, Newcastle Biomedical Research Centre and Unit, Newcastle upon Tyne Hospitals NHS Foundation Trust and Newcastle University. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health

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along with a wireless electro-oculography (EOG) device (Zerowire, Italy), which monitored horizontal eye movement. The Dikablis and EOG (sampling at 1000Hz) were synchronized using a 3D motion capture system (Vicon, Oxford, UK). Importantly for this study the 50Hz sampling rate of the Dikablis is adequate for the detection of saccades, although it may not be able to provide precise information on saccade durations or peak velocity as these features require higher sampling frequencies (>200Hz) [11-13].

The Dikablis uses a dual-camera system, with one monocular infra-red eye camera and one fish-eye field camera. With the use of a four point calibration, the video output from these cameras are overlaid with a cross hair provided on the video as a spatial view of pupil location. The raw co-ordinate data is derived from this cross-hair. Overall the Dikablis provided us with videos of the eye itself, the scene and a combination of the two with a cross-hair of pupil location. This enabled us to analyze the video data using the accompanying D-Lab software, which allowed selection of individual frames of the video (gold standard reference), so frame by frame analysis was possible.

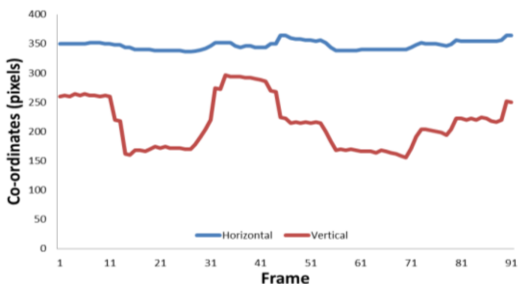

Figure 1. Example raw data from Dikablis mobile eye-tracker during walking

C. Procedure

Participants were asked to walk 5m in a straight line in the gait laboratory. They did this with and without a doorframe to walk through and repeated the same task several times for each condition. Eye movements were tracked during these walks in order to provide data on the visual sampling strategies employed by older adults and people with PD during a natural everyday task.

D. Feature Selection and Evaluation

Ten videos from each of the subjects (*n*=10) were visually inspected by a single examiner (SS) frame by frame, in order to compare to the algorithm results (100 videos in total). The number of visually detected saccades during the walking trials was recorded and then compared to the number measured by the algorithm.

To calibrate the visual inspection the participants began by making saccades between two markers set at 5° distance while sitting static. This was viewed and measured by the examiner prior to viewing the walking videos in order to provide a reference for the eye movement distance.

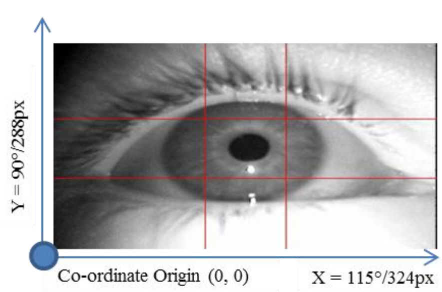

Figure 2. Eye view camera alignment and co-ordinates

E. Detection of visual events via algorithm

While a full representation the algorithm is presented in Figure 3, the following details the algorithm used for the mobile eye tracking data:

Stage 1: Distance, velocity and acceleration

Each parameter of interest was calculated for saccades and fixations, via a velocity based algorithm developed using MATLAB® 2012a (Mathworks, Natick, MA, USA) software. Firstly the algorithm begins by calculating the point to point position change of the *x* and *y* co-ordinates for each frame in the raw data (Figure 2), which provides a distance in pixels (1; where t1 and t2 refer to time point 1 and 2 respectively).

$$\text{Distance} = \sqrt{(x_{t1} - x_{t2})^2 + (y_{t1} - y_{t2})^2} \tag{1}$$

The velocities (2) and accelerations (3) are then calculated as the change in distance and change in velocity from one frame to the next (or previous).

$$\text{Velocity} = \left(\frac{\text{Distance}}{\text{Time}}\right) \tag{2}$$

$$\text{Acceleration} = \left(\frac{\text{Velocity}_{t1} - \text{Velocity}_{t2}}{\text{Time}}\right) \tag{3}$$

Stage 2(a): Conversion of pixels to degrees

The raw eye camera *x* and *y* co-ordinate data in pixels (Figure 2 and 3) was then converted to degrees, calculated using the pixel to degree conversion ratio of 1:0.31 (Table I).

TABLE I. EYE VIEW CAMERA CO-ORDINATE CONVERSION

	Eye view max pixels (px)	Eye view max degrees (°)	Eye view conversion (°/px)
X (horizontal)	384	115	0.30
Y (vertical)	288	90	0.31
X + Y	672	205	0.31

Stage 2(b): Removal of data caused by blinking and flicker

The raw data was filtered using set criteria for blinks and flickers, which were based upon the raw co-ordinate data and the velocities of the individual points. Blinks (closing of the eye) were classified as any frames that had co-ordinates equal to that of the origin (0, 0) and flickers were classified as any point to point movement with a velocity of over 1000°/sec or acceleration of over 100,000°/sec². These artefacts were removed from the data before any further analysis was performed and linear interpolation was used to fill in gaps after the removal of missing data.

Stage 3: Saccade and fixation detection

Following calculation of velocities and accelerations for each frame in the raw data the algorithm then classified each point above a certain velocity threshold (i.e. >240°/sec (5°)) as a saccade. A threshold above a 5° distance was chosen due to previous work using the same threshold for eye-tracking with EOG during walking [3]. This threshold was used to rule out most of the intrusions from other eye movements and provide purposeful eye movement data which was adaptable depending upon the task (i.e. lower threshold for static tasks). If the frame velocity did not reach the velocity threshold it was classified as a fixation.

An acceleration threshold (i.e. >3,000°/sec²) was then employed within the algorithm above which events would be classified as a *saccade* and below a *fixation*. Any saccadic durations longer than 5 frames (100ms) were discarded as saccades are not known to occur over this time threshold [11], and for similar reasons fixations less than 100ms were also discarded.

Once the saccade and fixation frames were located, the algorithm grouped together the fixation and saccade points that were next to one another. Saccade distances were then calculated by summing the distances of adjacent frames classified as saccades.

Stage 4: Quantifying saccades and fixations

Once the visual events had been detected the following features were extracted: Saccade number, frequency, velocity, amplitude, direction, duration and fixation frequency, duration and timing (Figure 3).

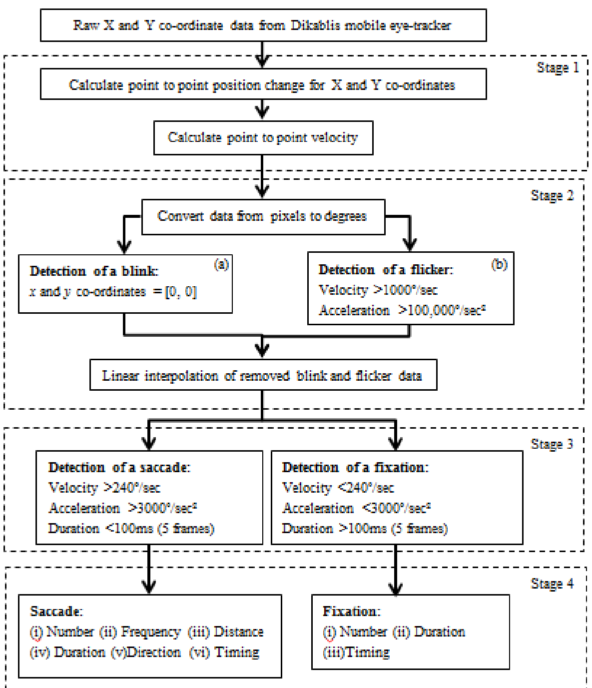

Figure 3. Algorithm flow chat

F. Data Analysis

Detection of a saccade via frame by frame video analysis was compared to output from the MATLAB® algorithm, with respect to the following criteria:

- Correct detection: Algorithm saccade detection was marked as correct if it was found in the corresponding video.
- Undetected: Algorithm saccade detection was marked as undetected if the saccade was found in the corresponding video, but not in the algorithm output.
- Spurious: Algorithm saccade detection was marked as spurious if it was in the algorithm output but not in the corresponding video.

Intra-class Correlations (ICC; 2,1 model) were quantified using SPSS (v21) to assess the absolute agreement of number of saccades detected by visual inspection and the algorithm.

IV. RESULTS

The results demonstrate that reliability was similar in PD subjects (n=5) (ICC(2,1); 0.940) compared to HC (n=5) (ICC(2,1); 0.941). The algorithm correctly detected an average of 81% of the saccades made while walking for HC and 85% for PD. Higher average undetected saccades were found for HC (17%) compared to PD (11%), but lower average spurious saccades were found for HC (2%) compared to PD (4%).

TABLE II. ALGORITHM PERFORMANCE: HC

Participant	HC1	HC2	HC3	HC4	HC5
Saccades – visual inspection*	34	35	23	5	29
Saccades – algorithm*	31	27	24	3	27
Correct detections: n (%)	31 (91)	26 (72)	22 (88)	3 (60)	27 (93)
Undetected: n (%)	3 (9)	9 (25)	1 (4)	2 (40)	2 (7)
Spurious: n (%)	0 (0)	1 (3)	2 (8)	0 (0)	0(0)

* Sum of saccades made over 10 trials.

TABLE III. ALGORITHM PERFORMANCE: PD

Participant	PD1	PD2	PD3	PD4	PD5
Saccades – visual inspection*	23	2	15	36	25
Saccades – algorithm*	21	2	16	28	22
Correct detections: n (%)	20 (83)	2 (100)	14 (82)	28 (78)	21 (81)
Undetected: n (%)	3 (13)	0 (0)	1 (6)	8 (22)	4 (15)
Spurious: n (%)	1 (4)	0 (0)	2 (12)	0 (0)	1 (4)

* Sum of saccades made over 10 trials.

VI. DISCUSSION

The present study was developed with the aim of providing and validating a simple algorithm for the detection of visual events such as saccades within mobile eye-tracking raw data (Figure 3). This is fundamental for accurate automated evaluation of eye-tracking data. Based on our experiences with the mobile eye-tracking data analysis performed with the developed algorithm, we believe its major advantage over other algorithms is that it is simple and easily implemented [2, 9]. The accuracy of velocity based algorithms has been shown to be lower than other algorithms such as dispersion thresholds [9, 10]. However, the balance of speed and precision with a velocity based algorithm makes it ideal for many applications such as eye tracking during dynamic tasks (i.e. analyzing eye-tracking data during walking).

Similar to previous work which assessed blink number during eye-tracking [14], frame by frame visual inspection of the eye movement videos from the experimental trials with ten different individuals served as the ground truth for evaluating the detection performance of the algorithm (Table 2).

Robustness across participants

For the experimental evaluation, participants performed the same walking tasks and data were analysed using the same fixed algorithm settings, comparing to visual inspection. Under these conditions, the algorithm developed for detecting visual events (i.e. saccades) in mobile eye-tracking data proved relatively robust, overall correctly detecting 194 out of 227 (85%) saccades made by the participants (n=10) during the walks (100 in total), with 33 undetected and 7 spurious detections (Table 2 and 3). The intra-class correlation coefficients (ICC, model 2,1) also demonstrate that the algorithm is highly reliable (overall ICC(2, 1) 0.937) when compared to the ground truth used in this study (visual inspection). For several participants, however, lower correct detection scores (72-80%) were seen because of more undetected and spurious events in their trials (Table 2 and 3). Upon further inspection of the raw frame by frame eye movement video data from these participants, it is clear that saccades were undetected due to several issues. One issue is flickering of the fixation cross hair with particular eye movements (i.e. vertical – looking down) and during blinks, a limitation of all infra-red eye-tracking devices [11, 13, 15]. These flickers and other data infiltrations would have been picked up in the visual inspection but would have been discounted in the algorithm. Another possible issue is that HC2, HC4, and PD4 had corrected vision via glasses or contact lenses, which are known to impact eye-tracking data quality as they cause infra-red light refraction making pupil detection difficult [11]. Although several of the other participants (PD1, PD3 and PD5) also had corrected vision, the data quality may still have been affected. The rare spurious saccade detections likely occurred due to other eye-movements such as VOR infiltrating the data, a problem not encountered while recording static eye-tracking. These could further be controlled for by recording head movement during walking [16].

Still, the achieved detection performance demonstrates that the algorithm is adequate for saccadic eye movement analysis carried out during the walking protocols performed by the participants.

Study Limitations

One limitation of the current work is that during visual inspection it was difficult to accurately measure saccade amplitude. The algorithm detects movement of the pupil cross-hair over 5° amplitude (i.e. >240°/sec velocity threshold) and is capable of ruling out other movement of the cross-hair via set criteria. During calibration the examiner was able to view and measure 5° movement of the cross hair made by each participant prior to analyzing the walks. However, it remained difficult for the examiner to differentiate between movements of slightly lower distance using the video/still images alone. This may be why many of the visual inspection saccade numbers are higher (Table 2). Future work could improve this by using a lower velocity threshold (i.e. 2-3° amplitude) [17], although this may allow further data intrusions from other eye movements (i.e. VOR) in the algorithm output.

Few studies are available that provide mobile eye-tracker data analysis algorithm validation, as testing algorithms against a ground truth (such as visual inspection) is time consuming. As a result we had little basis to develop a methodology to evaluate our algorithm. Although visual inspection has been used in this study other possibly more appropriate ground truth comparisons should be carried out on further representative samples. For example; comparison to simultaneously recorded electro-oculography (EOG) or recording of eye movements between targets at set distances while walking, which have been carried out in previous static studies [2, 18]. This will build on our initial work allowing further validation of visual event detection algorithms in mobile eye-tracking data, which is necessary due to the impact algorithms have on further analysis [9].

V. CONCLUSION

This work provides a simple and robust algorithm for detecting visual events, such as saccades, from raw mobile eye-tracker data obtained during walking tasks. Future work should further validate this algorithm and eye-tracking device against other gold standard references such as EOG or set distance eye movements.

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