A Ground-Truth Data Set and a Classification Algorithm for Eye Movements in 360-degree Videos

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ABSTRACT

The segmentation of a gaze trace into its constituent eye movements has been actively researched since the early days of eye tracking. As we move towards more naturalistic viewing conditions, the segmentation becomes even more challenging and convoluted as more complex patterns emerge. The definitions and the well-established methods that were developed for monitor-based eye tracking experiments are often not directly applicable to unrestrained set-ups such as eye tracking in wearable contexts or with head-mounted displays. The main contributions of this work to the eye movement research for 360° content are threefold: First, we collect, partially annotate, and make publicly available a new eye tracking data set, which consists of 13 participants viewing 15 video clips that are recorded in 360°. Second, we propose a new two-stage pipeline for ground truth annotation of the traditional fixations, saccades, smooth pursuits, as well as (optokinetic) nystagmus, vestibulo-ocular reflex, and pursuit of moving objects performed exclusively via the movement of the head. A flexible user interface for this pipeline is implemented and made freely accessible for use or modification. Lastly, we develop and test a simple proof-of-concept algorithm for automatic classification of all the eye movement types in our data set based on their operational definitions that were used for manual annotation. The data set and the source code for both the annotation tool and the algorithm are publicly available at https://web.gin.g-node.org/ioannis.agtzidis/360_em_dataset.

1 INTRODUCTION

Eye tracking offers a non-invasive insight into the underpinnings of the human visual system, its mechanisms of perception and processing. The holy grail of eye tracking would be to enable pervasive accurate monitoring of gaze direction and targets, as well as the situational context, in everyday life. While this is still unrealistic, there are several ways of approaching it already. One is creating lightweight eye tracking glasses, and several models have recently become commercially available[1][2][3]. These also capture the potential gaze targets with a scene camera, but dealing with the real world is difficult: The camera recordings will be affected by motion blur from head movements and locomotion, direct sunlight, etc. Also, only part of the full context can be captured by the scene camera.

Another approach to carrying out eye tracking experiments that are close to the real-world studies is utilising head-mounted displays (HMDs) to substitute (or augment) reality with content of varying degree of controlledness: From simplified programmatically generated stimuli, to interactive rich environments, or full-360° recordings of the real world. Immersion of virtual reality (VR) and HMD content depends on a variety of factors [Cummings and Bailenson 2016; Jennett et al. 2008] and is not fully understood yet, but some realism is likely sacrificed in order to gain a higher degree of control and relative ease of analysis.

Here, we wanted to precisely characterise eye movement behaviour in a scenario that is as unconstrained as possible. We therefore presented 360° videos in an HMD with integrated eye tracking, which enabled us to approach the naturally occurring complexity of reality, while maintaining some degree of control over the audiovisual content. Such videos are naturally affected by lighting artefacts and camera motion, but they can be quality-checked before presentation, and head motion-induced blur is not present.

In any eye tracking set-up, however, there persists a major challenge – accurately and robustly classifying the eye movements. In the case when the participant's head motion is restricted (e.g. by a chin bar), the types of eye movements are mostly well understood, though not as well as we would like to believe [Hessels et al. 2018], since researchers often disagree on fundamental definitions for fixations and saccades. Further complications arise when smooth pursuit (SP) is introduced into the mix because it is often thought of as a "fixation on a moving target" even though it can reach high speeds [Meyer et al. 1985]. Detecting SP algorithmically is notably a more challenging endeavour than detecting fixations and saccades, even for state-of-the-art algorithms [Larsson et al. 2016; Startsev et al. 2018]. The distinction between various eye movements becomes even more complex when the head of the recorded participant can move freely. There are no commonly used definitions in this area of research, and [Hessels et al. 2018] urge the community to make their eye movement definitions explicit, since currently the algorithmic approaches for "fixation" detection in VR or mobile eye tracking imply very different underlying interpretations of this eye movement type, and comparing studies with different definitions is impossible or, at the very least, confusing. In VR, for example, the TobiiPro software[4] is using dwells on the same VR object (by intersecting the gaze ray with the virtual scene) as a substitute for fixations (very similar to I-AOI [Salvucci and Goldberg 2000]), while their own mobile and even 360° video-based[5] eye tracking solutions use simple speed thresholding [Olsen 2012]. This means that the implied fixation definitions in the two cases differ wildly: The first would replace all pursuits with fixations, whereas the second should not accept SP in place of fixations.

Overall, eye movement detection lacks precise definitions and is very fragmented: Researchers focus on detecting certain eye movement types in isolation [Agtzidis et al. 2016b; Behrens et al.

[1]https://www.tobiipro.com/product-listing/tobii-pro-glasses-2/
[2]https://pupil-labs.com/pupil/
[3]https://www.ergoneers.com/en/hardware/dikablis-glasses/
[4]https://www.tobiipro.com/product-listing/vr-analytics/
[5]https://www.tobiipro.com/product-listing/tobii-pro-lab/

2010; Steil et al. 2018], thus potentially missing important relations between them. The data sets that are assembled for such works, especially with VR or mobile eye tracking, are scarce and often specialised: E.g. [Santini et al. 2016] use mobile eye tracking, but without head motion and only with synthetic stimuli; [Steil et al. 2018] annotate gaze target similarity and not the actual eye movements; [John 2017] touches on the difficulty of understanding and annotating eye movements during head or body motion, but does not explicitly define the labelled eye movement types.

The contributions of our work are as follows: We recorded and made publicly available a data set of eye tracking recordings for dynamic real-world 360° video free-viewing as well as for one synthetic video clip, where eye movements are inferred more easily. Our data total ca. 3.5 h of recordings. We developed a two-stage manual annotation procedure that labels (in line with typical expert annotations) fixations, saccades, and pursuits, as well as higher-level concepts that describe eye-head coordination (vestibular-ocular reflex – VOR and pursuing with head movement only) or interaction of several "basic" eye movement types, such as (optokinetic) nystagmus (OKN). We implemented this procedure by extending the open-source eye tracking data labelling interface of [Agtzidis et al. 2016a] for eye movement annotation with 360° content. With its help, we manually annotated a part of the collected data (ca. 16%, two representative observers per clip), which already allows for the evaluation of algorithmic labelling approaches. We attempted to give operational definitions to all the labelled eye movements and provide both a theoretical and a data-driven basis for future research. Based on the principles underlying our manual annotation, we also devised a simple unified framework for algorithmically detecting all the eye movement classes we defined. To the best of our knowledge, this is the first combination of a data set and a framework to attempt systematically labelling all major occurring eye movement types in a unified fashion. Our algorithm is also the first eye movement detection method that combines information from both eye-in-head and eye-in-world frames of reference.

2 RELATED WORK

As the contributions of this work are tightly related to eye tracking set-ups with unrestricted head rotation, we mostly focus on the works in the same domain, including mobile and VR eye tracking.

2.1 Data Sets and Eye Movement Annotation

For egocentric or 360° content, only few data sets are available that provide raw eye tracking data so far. Even fewer studies supply manual annotations or develop an algorithmic detection strategy for the eye movements in this context. Saliency in 360° [Cheng et al. 2018; Gutiérrez et al. 2018; Nguyen et al. 2018] as well as egocentric [Lee et al. 2012; Li et al. 2018; Polatsek et al. 2016] content is gaining popularity, and this inevitably requires the collection of eye tracking data for 360° images and videos or in the mobile eye tracking scenario. However, the data sets that are typically published provide scanpaths in the form of sequences of "fixations" [Bolshakov et al. 2017; David et al. 2018; Rai et al. 2017; Sitzmann et al. 2018], which limits their usefulness for eye movement research. Also, while the frequency of the eye tracker is not that important for saliency analyses, higher-frequency data that is available with modern eye trackers enables much finer-grained eye movement detection. [Damen et al. 2014; Santini et al. 2016], for example, provide the eye tracking data at 30 Hz only.

[Santini et al. 2016] use mobile eye tracking, but restrict the participants' movements with a chin bar and do not project the gaze coordinates onto the scene camera feed. The diversity of this data set is limited by the synthetic nature of the stimuli. [Steil et al. 2018] annotate the data for their own definition of fixations, which does not necessarily correspond to the eye movements themselves: The annotators were labelling sequences of dwells on real-world objects, regardless of whether these objects were moving or whether the observer's head was in motion. [Fischer et al. 2018] use mobile eye tracking to validate a remote imaging-based eye gaze estimation approach only, without analysing the eye movements. [Lo et al. 2017] only capture the head rotation data without any eye tracking, assuming that the object at the centre of the participant's field of view is the one being looked at. [Polatsek et al. 2016] seem to use the term "fixation" interchangeably with "gaze point".

[Löwe et al. 2015] designed a visualisation interface for multi-viewer gaze similarity for 360° content analysis. This is, however, not a tool for eye movement annotation or analysis. [John 2017; Kothari et al. 2017] manually annotated eye movements in recordings with a wearable eye tracker during locomotion and ball catching. The head motion was reconstructed with the data from a six-axis inertial measurement unit. During the annotation, the head and the eye-in-head speeds were displayed alongside the feed from the eye and scene cameras (with the gaze projection marked with a cross). The authors labelled fixations, pursuits, saccades, and blinks, but no explicit eye movement definitions that were used for manual annotation are given. In general, this labelling method takes into account both the eye-in-head and the eye-in-world movements, but only implicitly – through comparing the eye and head speeds or by inferring the gaze point motion on the scene camera frames. This makes it harder for the experts to understand the precise nature of the eye movement, especially when the participant, their gaze, and the scene objects are all moving at the same time.

In comparison to previously published works, our data set is relatively high-frequency (120 Hz), provides the raw (re-calibrated) eye tracking recordings, and is (partially) manually annotated with explicit definitions of the labelled eye movements. In addition to the typically considered set of fixations, saccades, and pursuits, we annotate instances of VOR and OKN, as well as pursuits of objects performed with the head only (no eye-in-head movement). Our annotation process takes advantage of a two-stage pipeline, where only eye-in-head motion is considered during the first stage, and the labelling is refined with the reference to eye-in-world motion during the second stage. This allows the annotator to access all available information about the recorded signal sequentially instead of all at once, thus simplifying the procedures of the individual stages.

2.2 Algorithmic Detection

Most of the algorithms so far have been developed with monitor-based experiments in mind (due to their prevalence in research to date). Therefore, they cannot distinguish whether the provided gaze recordings are in the coordinate system relative to the head (i.e. eye-in-head gaze) or relative to the world (eye-in-world gaze). The frame of reference of the ensuing gaze data analysis, therefore, usually depends on the recording type: For wearable eye trackers (mobile or integrated into an HMD), eye-in-head gaze is commonly analysed, for fixed eye trackers – eye-in-world (e.g. gaze on the monitor).

The built-in algorithms for two of the most popular wearable eye trackers use only the eye-in-head frame of reference for saccade and fixation detection. The TobiiPro software uses a speed-based I-VT filter [Olsen 2012] when the Tobii Pro Glasses 2 eye tracker is used. The Pupil Labs headset uses a modified [Barz 2015] version of the gaze dispersion-based algorithm I-DT [Salvucci and Goldberg 2000] and simply handles gaze direction vectors instead of on-screen coordinates. [David et al. 2018] also use a version of I-VT in the frame of reference of the head, and [Sitzmann et al. 2018] use I-DT in the frame of reference of the virtual environment.

These simplified approaches will necessarily mislabel eye movement types in the presence of head motion, which is often present in unconstrained scenarios. In our data, for example, 48% of the time the head was moving with a speed of at least $10°/s$. Since the Tobii Pro Glasses 2 are equipped with a gyroscope, augmented by [Hossain and Miléus 2016] to account for head motion (not yet used in the software shipped to the user). The approach of [Kinsman et al. 2012] compensates for ego-motion by using the movement information obtained from the scene camera (this is a more widely applicable, but less precise approach compared to using sensor data).

In their respective approaches, [Anantrasirichai et al. 2016] and [Steil et al. 2018] define fixations as maintaining gaze on an object in the world, regardless of head movement, locomotion, and object motion. This definition, similar to labelling virtual object dwells, mixes up dynamic and static eye movements and does not account for the interplay of head and eye movements, though slightly different mechanisms are at work during coordinated head-eye actions [Angelaki 2009; Fang et al. 2015]. [Steil et al. 2018] use a purely image-based technique, which computes the similarity score of the scene camera frame patches around subsequent gaze locations with a pre-trained deep network [Zagoruyko and Komodakis 2015]. They assign "fixation" labels to gaze samples that correspond to the patches that are similar (above a certain threshold) to the patch of the previous gaze sample. [Anantrasirichai et al. 2016] combine some pre-trained deep network-based features at the gaze location with position-derived statistics in order to detect fixations.

Optokinetic nystagmus (OKN) is a relatively easily-detectable eye movement pattern, and the algorithm of [Turuwhenua et al. 2014] first splits the input signal into fast and slow phases, then detecting episodes of OKN when the gaze moves in roughly opposite directions during the fast and slow phases.

Typical papers on eye movement detection focus on a certain aspect of the data, or even a certain eye movement type [Agtzidis et al. 2016b; Larsson et al. 2016; Turuwhenua et al. 2014]. It has been noted before that not labelling some eye movement types likely leads to poorer detection of the others (false detections that could not be attributed to any other class) [Andersson et al. 2017]. In contrast to this, we attempted to develop a universal eye movement labelling scheme that is based on the definitions of the eye movements, which we provide in this work, as these can differ wildly and unexpectedly from researcher to researcher [Hessels et al. 2018; Hooge et al. 2017].

3 DATA SET COLLECTION

Gathering a data set of eye tracking recordings for 360° equirectangular videos differs from the common monitor-based experiments. The experimental set-up, the choice criteria for the used stimuli, as well as the way of accounting for drifts during recordings are all influenced by the stimulus type. We explain our choices and describe the full data collection procedure below.

3.1 Hardware and Software

For data gathering we used the FOVE[6] virtual reality headset with an integrated 120 Hz eye tracker. For video presentation we used the integrated media player of SteamVR[7], which supports 360° content (we used equirectangular video format). A small custom C++ program was used to handle the eye tracking recordings and store them to disk. The data we stored for each recording includes (i) x and y coordinates of the gaze point on the full 360° video surface in equirectangular coordinates, (ii) the same x and y coordinates of the head direction, as well as its tilt. This allowed us to disentangle the eye motion from the head motion (computing the eye-in-head motion) and to reconstruct the gaze position in each participant's field of view. We also stored (as metadata) the dimensions of the headset's field of view (in degrees and in pixels).

We kept the original sound of the presented videos. In all clips but two it corresponded to the environment noises (the two exceptions had silence and an overlaid soundtrack). Sound has a bearing on eye movements during monitor-based video viewing [Coutrot et al. 2012], and should affect the viewers even more in virtual environments as noises may induce head rotation towards video regions that would otherwise never be in the field of view.

In our experimental set-up the participants were sitting on a swivel chair with the headset and headphone cables suspended from a hook above them. This allowed the subjects to swivel on the chair freely, without the interference of the cords, which could have otherwise led them to avoid head rotation. In addition to the discomfort of feeling the attached cables, unless those are suspended from above, their stiffness would have likely caused the displacement of the headset relative to the observer's head during the experiment, thus lowering the quality of eye tracking recordings.

3.2 Stimuli

The collection of videos we assembled includes 14 naturalistic clips we chose from YouTube and one synthetically generated video. All the naturalistic data are licensed under the Creative Commons license[8]. We give attribution to the original creators of the content by providing the Youtube IDs of the original videos together with our data set. The selected clips represent different categories of scene content and context, e.g. static camera, walking, cycling, or driving, as well as such properties as the content representing an indoors or an outdoors scene, the environment being crowded or empty, urban or mostly natural. The durations of the complete videos varied greatly, and we decided to use a maximum of one minute per

[6] https://www.getfove.com
[7] https://store.steampowered.com/steamvr
[8] The license used by YouTube is the more permissive version of Creative Commons – https://creativecommons.org/licenses/by/3.0/legalcode – and allows reuse, remix, and distribution of the original work with attribution to the original creator.

Table 1: Video Stimuli

Video Name	Categories	Duration
01_park	static camera, nature, empty	1:00
02_festival	static camera, urban, busy	1:00
03_drone	drone flight, urban, very high	1:00
04_turtle_rescue	static camera, nature, busy	0:38
05_cycling	cycling, urban, busy	1:00
06_forest	walking, nature, empty	1:00
07_football	static camera, nature, busy	1:00
08_courtyard	static camera, urban, busy	1:00
09_expo	static camera, indoors, busy	1:00
10_eiffel_tower	static camera, urban, busy	0:57
11_chicago	walking, urban, busy	1:00
12_driving	car driving, urban, busy	1:00
13_drone_low	drone flight, urban, empty	1:00
14_cats	static camera, urban, busy	0:43
15_synthetic	moving target	1:25

stimulus. For each of these clips, we extracted a continuous part of the original recording that contained no scene cuts to preserve the immersion. The details for each video (name, categories somewhat describing the scene, duration) are listed in Table 1.

In addition, we generated one stimulus clip synthetically for a more controlled scenario. The circular gaze target we used for this part of the experiment followed the recommendations of [Thaler et al. 2013] in order to improve fixation stability. It measured two degrees of visual angle in diameter and was displayed in white on a black background. For simplicity, we neglected the idiosyncrasies of the equirectangular format for the stimulus generation here, as the target always stayed close to the equator of the video, meaning that shape distortions would be small.

The synthetic clip we generated consisted of five phases. Each phase had a short instruction set displayed (for ca. 7 s) before the fixation gaze target appeared. The first four phases lasted 10 s after the stimulus appeared and were designed (together with their respective instructions) to induce (i) eye movements that are typically seen in controlled lab settings: fixations, saccades, and smooth pursuit, without excessive head motion, (ii) VOR with voluntary head motion while maintaining a fixation on a stationary target, (iii) "natural" long pursuit, without any additional instructions (an arbitrary combination of body or head rotation, VOR, and smooth pursuit), where the target moved with a constant speed of $15^\circ/s$, covering 150°, and (iv) a special combination of VOR and smooth pursuit, when the eyes are relatively stationary inside the head, but the gaze keeps track of a moving target. We refer to the latter type of eye-head coordination as "*head pursuit*". During the fifth phase, OKN was induced by targets rapidly moving for a short period of time (at $50^\circ/s$ symmetrically around the centre of the video), disappearing, and then repeating the motion, covering 25° on each pass. Both left-to-right and right-to-left moving targets were displayed with a brief 2.5 s pause between the sequences of same-direction target movement (5 s each).

3.3 Experimental Procedure

In order to be able to detect and potentially compensate for eye tracking quality degradation, we added a stationary fixation target at the beginning (for 2 s) and the end (for 5 s) of each video clip. Overall, the 15 videos have a cumulative duration of ca. 17 minutes including these fixation targets. The recording process was split into three sessions for each participant. During the first and the second sessions, 7 naturalistic videos were presented in succession. The last session only included the synthetic video. The participants could have an arbitrary-length break between the sessions. The eye tracker was calibrated through the headset's built-in routine shortly before every recording session. We then empirically and informally validated the calibration using the FOVE sample Unity project[9] where the participant's gaze is visualised. If the quality was deemed insufficient, the calibration procedure was repeated. We accounted for eye tracking drifts between recordings of the same session by performing a one-point re-calibration with the fixation target at the beginning of each video.

The naturalistic videos were presented in a pseudo-random order (same for all subjects); the synthetic clip was presented last not to prompt the observers to think about the way they moved their eyes before it was necessary. If the participant at any point was feeling unwell, the recording was interrupted. Afterwards, a new calibration was performed, the unfinished video was skipped, and the recording procedure was continued from the next clip.

Overall, we recorded gaze data of 13 subjects, and the number of recordings per stimulus video clip was between 11 and 13 (12.3 on average), which amounts to ca. 3.5 h of eye tracking data in total.

4 MANUAL ANNOTATION

When working with 360° equirectangular videos, the natural visualisation of the recording space is the camera (or the observer's head) placed at the centre of a sphere that is covered by the video frame pixels. Computationally, this directly matches the equirectangular video representation, where the x and y coordinates on the video surface are linearly mapped to the spherical coordinates of this sphere (longitude and latitude, respectively). Since the field of view is limited (up to 100° in our HMD), the observers will use head rotation (as in everyday life) to explore their surroundings, so this aspect of the viewing behaviour needs to be accounted for both in the definitions of the eye movements and the annotation procedure.

4.1 Definitions

In order to fully describe the interplay of the movement of the head and the eyes themselves, we cannot assign just a single eye movement label to every gaze sample, since the underlying process may differ when eye-head coordination is involved. Therefore, we used two labels for each gaze sample, to which we refer as *primary* and *secondary* labels. Following the recommendations of [Hessels et al. 2018], we defined the eye movements that we annotated below to avoid potential confusion in terminology. As researchers can disagree on the nature and purpose of various eye movements [Hessels et al. 2018], we do not argue that the ones we used for this work are the ultimately correct ones, but we hope that this would provide a starting point for further refinement and investigation.

[9]https://github.com/FoveHMD/FoveUnitySample

We did not include post-saccadic oscillations or microsaccades in our annotations as the wearable eye tracker frequency and precision did not permit their confident localisation by the annotator.

Primary label is necessarily assigned to *all* gaze samples, and can be one of the following:

- *Fixation*: A period of time where no movement of the eye inside the head is triggered by retinal input (but may e.g. reflexively compensate for head motion).
- *Saccade*: High-speed ballistic movement of the eye to shift the point of regard, thus bringing a new (part of an) object onto the fovea (including adjusting the gaze position to match the tracked object via catch-up saccades during pursuit, or similar).
- *Smooth pursuit (SP)*: A period of time during which the eyes are in motion inside the head and a moving (in world coordinates, relative to the observer) target is being foveated.
- *Noise*: Even though noise is not an actual eye movement type, we accumulate blinks, drifts, tracking loss, and physiologically impossible eye "movements" under this one name.

The *secondary* labels describe in more detail how the primary eye movements were executed and are mostly a consequence of head motion (except for OKN). The following labels are possible:

- *Vestibulo-ocular reflex (VOR)*: A period of time when the eyes are compensating for head motion and stabilising the foveated area.
- *Optokinetic nystagmus (OKN) or nystagmus*: Sawtooth-like eye movement patterns, which are composed of fast saccadic parts alternating with slow stabilisation parts. We assigned the label of OKN to all such patterns, though it has to be noted that some of the OKN labels correspond to nystagmus, e.g. when a participant is observing a blank part of the synthetic stimulus while simultaneously turning the head, so the reflexive movement is not actually triggered by the visual input.
- *VOR + OKN*: This is a combination of the two previous categories: The eye signal exhibits a sawtooth pattern during head rotation.
- *Head pursuit*: A period of time where a pursuit of a moving target is performed only via head motion, with the gaze direction within the head relatively constant.

Unlike the *primary*, the *secondary* label can easily be unassigned even in large windows of gaze samples (e.g. foveating a stationary or moving object in the scene without head motion).

4.2 Labelling Procedure

To thoroughly describe the labelling process, we focus primarily on the information that was available to the manual annotator. We implemented a two-stage annotation pipeline, with stages corresponding to different frames of reference (for the visualised gaze speed and coordinates), sets of assigned labels, and projections used for the scene content display. We refer to these stages (or modes of operation) as *field of view* and *eye+head*.

In the *field of view (FOV)* mode, the annotator is presented with the view of the scene that is defined by the corresponding head rotation of the subject (the size of the visualised video patch roughly corresponds to the field of view that the participant had in the VR headset). This view corresponds to the frame of reference that moves together with the participant's head and allows us to see the actual visual stimulus that was perceived by the participant.

In the *eye+head (E+H)* mode, the full equirectangular video frame is presented to the annotator. Visualising gaze locations in this view enables the annotator to see the combination of the head and eye movement, which corresponds to the overall gaze in the world (or 360° camera, to be more precise) frame of reference.

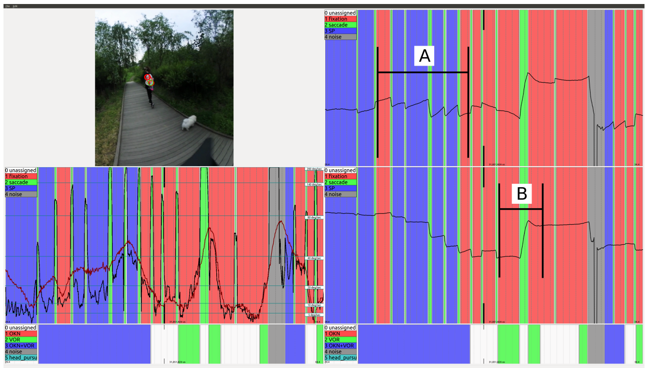
In both operation modes, the currently considered gaze sample as well as previous and future gaze locations (up to 100 ms) are overlaid onto the displayed video surface. In addition, the plots of the x and y gaze coordinates over time, as well as the plot of both the eye and the head speeds are presented (see Figure 1a and 1b for the FOV and E+H mode examples). The coordinate systems used for these plots, however, differ between the two modes: In the FOV mode, the gaze coordinates and the speed of gaze are reported in the *head*-centred coordinate system, whereas in the E+H mode, the coordinates and the speed in the *world* coordinate system are visualised. This way, the FOV representation provides the annotator with the eye motion information within the eye socket, while the E+H representation is responsible for highlighting the absolute movement of the foveated objects, which is necessary for determining the precise label type, e.g. distinguishing between fixations and pursuits.

The manual annotator began (i.e. *the first stage*) with the FOV operation mode and assigned all primary eye movement labels without taking head motion into account: Ballistic eye-in-head motion would correspond to saccades, relatively stationary (in the coordinate system of the head) gaze direction – to fixations, smoothly shifting gaze position – to pursuits (provided that a correspondingly moving target exists in the scene), etc. To speed up the process, we pre-labelled saccades with the I-VT algorithm of [Salvucci and Goldberg 2000], applied in the FOV coordinates (instead of the coordinates of the full equirectangular video) with a speed threshold of $140°/s$. The labeller then went through each recording, correcting saccade limits or inserting missed ones, assigning fixation, SP, and noise labels, inserting new events where necessary. OKN was labelled in this stage as well, because the sawtooth pattern of eye coordinates was more visible without the head motion effects.

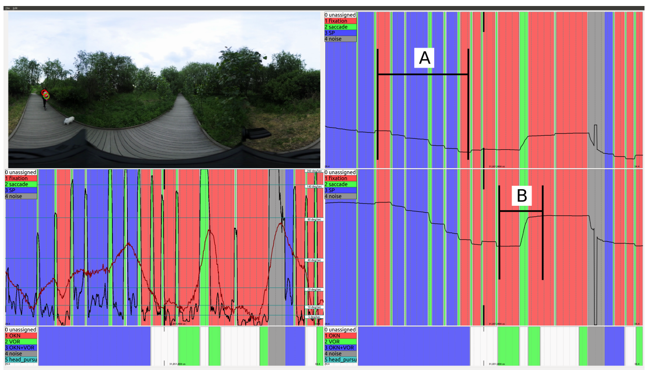
After the annotator felt confident about the first labelling stage results, *the second stage* would begin: The annotator went through the video again, this time – in the E+H operation mode. On the second pass, the previously assigned primary labels were visible and needed to be re-examined in the context of the eye-head coordination, with respective additions of the secondary labels:

- *SP to fixation*: If the primary SP label of the first stage corresponded to the foveation of a stationary (in world coordinates) target, the label was changed to a fixation, and a matching VOR episode was added to the secondary labels. If the SP episode in question belonged to an OKN episode, the respective part of the latter was re-assigned to the OKN+VOR class.
- *Fixation + head pursuit*: If the primary fixation label of the first stage (i.e. little to no movement of the eye within its socket) corresponded to following a moving (in world coordinates) target, the secondary "head pursuit" label was added.
- If the primary SP label was maintained in the second stage in the presence of head motion, a VOR episode was added to the secondary labels.

The annotation was performed by an experienced eye movement researcher (one of the authors), who first annotated five minutes of pilot data in order to familiarise himself with the procedure and the



(a) FOV mode



(b) E+H mode

Figure 1: Schematic of field-of-view (a) and eye+head (b) operation modes. Differences in the patterns of gaze coordinates and speeds allow for improved annotation. "A" and "B" marks are for reference only (not shown during annotation). Coloured intervals correspond to different primary (on three large panels) and secondary (bottom) labels.

interface; ambiguities were discussed with the co-authors. Labelling a single recording (of about a minute of gaze data) took between 45 min and 1 h. In total, our annotations cover about 16% of the data (two recordings per stimulus clip) and amount to ca. 33 min.

4.3 Labelling Tool

Some previous works prefer to hide the stimulus from the annotator [Larsson et al. 2013] not to bias the rater's expectation of which eye movements are more likely or possible with a given stimulus. We argue, however, that since we are more interested in accurate labelling than in stimulus-agnostic distinguishability of the eye movements, providing all the available relevant information is an essential step. Without the video frames, it would be impossible to distinguish e.g. pursuits and drifts.

In order to implement our manual annotation pipeline we significantly extended the publicly available[10] hand-labelling tool of [Agtzidis et al. 2016a], adding the support for simultaneous primary and secondary label assignment and the field-of-view (FOV) operation mode, where the displayed video "re-enacts" the participant's head movements during the recording session (see Figure 1a).

For both stages of the labelling process, our interface included six panels (see interface examples in Figure 1): The top left panel displays the video (either the FOV representation or the full equirectangular frame) overlaid with gaze samples. The panel below it displays the speed of gaze (in black) in the respective coordinate system – head-centric for the FOV mode and the video coordinate system in the E+H mode – and the speed of the head movement (in red). The two top panels on the right visualise the x and the y gaze coordinates over time (again, the coordinate system depends on the operation mode). The speed and coordinate panels colour-code the time intervals according to the assigned primary label. The two bottom panels are identical and serve the purpose of visualising the secondary labels. This information is duplicated in order to give the annotator the possibility to easily adjust the VOR and head pursuit intervals based on both the head speed plot and the plot of the gaze coordinates (e.g. verifying that the gaze direction is relatively constant in the world coordinates, but the head is turning).

Despite the multitude of panels in the interface, only a subset was used to make the vast majority of decisions: Gaze coordinate panels were mostly sufficient for primary and secondary label assignment. The speed and video panels were referred to in case of uncertainty.

Figure 1 also illustrates the differences of gaze patterns in the two representations we use. For instance, the sawtooth pattern that can be observed in FOV view close to the beginning of the displayed gaze sequence changes shape in the E+H mode and becomes rather step-shaped (regions marked with "A" in the figure). Also note how the head and eye movements cancel out each other during a fixation that is combined with VOR (regions marked with "B", corresponding to the VOR labels on the two bottom panels in Figure 1): The speeds are almost equal in the FOV mode (Figure 1a), and the eye in the world coordinate system is almost stationary (Figure 1b).

5 EYE MOVEMENT DETECTION ALGORITHM

We now describe a rule-based eye movement classification algorithm that is almost a direct formalisation of the eye movement definitions we consider in Section 4.1. It assigns primary and secondary labels to every gaze sample (potentially "unassigned" for the secondary labels) by analysing the same gaze and head movement information that was available to the manual annotator.

We first detected the saccades by analysing the E+H speeds with the two-threshold algorithm of [Dorr et al. 2010], which avoids false detections while maintaining high recall by requiring each saccade to have a peak gaze speed of at least $150°/s$, but all surrounding samples with speeds above $35°/s$ are also added to the detected episode. We did not use the FOV speed of gaze as it is influenced by head motion and can easily reach speeds above 100°/s when the eyes compensate for fast large-amplitude head rotations.

Afterwards, blinks were detected by finding the periods of lost tracking and extending them to include saccades that were detected just prior to or just after these periods, as long as the saccades were not farther than 40 ms from the samples with lost tracking.

We then split the remaining intersaccadic intervals into non-overlapping windows of 100 ms and classified each such interval

[10] https://www.michaeldorr.de/gta-vi/

Table 2: Threshold Values

Name	Used for	Threshold	Optimised
θ^{low}_{sacc}	saccades	35°/s	✓
θ^{high}_{sacc}	saccades	150°/s	✓
θ^{low}_{gaze}	fix., SP, VOR, head purs.	10°/s	✓
θ^{high}_{gaze}	fix., SP, VOR, head purs.	65°/s	✓
θ^{low}_{head}	VOR, head purs.	7°/s	-
θ^{high}_{head}	scaling $\theta^{\{low,high\}}_{gaze}$	60°/s	-

Table 3: Classification Performance on the Test Set

		Sample F1			Event F1		
	EM type	Comb.	FOV	E+H	Comb.	FOV	E+H
Primary	Fixation	0.911	0.867	0.900	0.897	0.808	0.890
	Saccade	0.813	0.737	0.813	0.899	0.865	0.899
	SP	0.381	0.128	0.362	0.288	0.153	0.293
	Noise	0.758	0.743	0.758	0.744	0.729	0.742
Secondary	OKN	0.205	-	-	0.085	-	-
	VOR	0.600	-	-	0.636	-	-
	OKN+VOR	0.664	0.614	0.647	0.577	0.626	0.620
	Head Purs.	0.546	-	-	0.204	-	-

independently. For this, we calculated the speeds of the head and the eye (relative to the head and the world) as the distance covered from the beginning to the end of the window divided by its duration.

To formalise the concepts of "stationary" and "moving" head cases, we used a speed threshold of $7°/s$. For the gaze speeds, we applied the low and the high thresholds of $10°/s$ and $65°/s$, respectively (both for the eye-in-head and the eye-in-world speeds) in order to distinguish slow, medium, and fast movements. As gaze stability decreases with head motion [Ferman et al. 1987], we scaled the gaze speed thresholds according to the speed of the head: $thd_{\text{scaled}} = (1 + v_{\text{head}}/60) * thd$, where $60°/s$ is the "reference" speed of the head. This means that if the head was moving at e.g. $30°/s$, the gaze speed thresholds were increased by 50%.

A fixation was always labelled when the E+H speed was below the low gaze speed threshold. If the head speed was above the corresponding low threshold, a secondary VOR label was assigned.

Pursuit-type eye movement labels were assigned when the E+H speed was between the low and the high gaze speed thresholds, unless the eye-in-head speed was above the high threshold (in which case, a noise label was assigned). However, there are different label combinations possible here: (i) *Head pursuit* in combination with the primary label of *fixation* was assigned when the FOV (eye-in-head) speed was below the low threshold and the head speed was above its own low threshold; otherwise, (ii) *smooth pursuit* in combination with *VOR* was detected when the head speed was above the low threshold, which implied that the head and the eyes were working in tandem (presumably, to follow a moving object); (iii) *smooth pursuit* without any secondary eye movement type was assigned when the head speed was below its low threshold, meaning that the eyes did not have to compensate for the head movement.

For the samples that did not fall into any of the previously listed categories it was then known that they had very high speed but were assumed not to be a part of any saccade (since saccades were detected already). Consequently, the noise label was assigned.

Overall, our approach uses five speed thresholds (plus a scaling parameter), and thus we refer to our algorithm as I-S^{5}T, *identification by five speed thresholds*. An overview of the parameters is given in Table 2: two thresholds for saccade detection, two to quantise eye speeds (scaled by head speed), and one to determine if the head is moving sufficiently to justify a potential VOR label. The used values for the first four of these were optimised using a grid-search procedure on the entire annotated data set, as we were interested in determining the upper-bound of what can be achieved with a simple detection algorithm in this relatively complex task, rather than in finding a well-transferable set of precise threshold values.

We also implemented an algorithm for detecting OKN (or nystagmus), with its sawtooth pattern of gaze coordinates. This pattern is easier to detect in the FOV gaze data as it often occurred during high-amplitude head motion in our data. The idea behind our detector is similar to [Turuwhenua et al. 2014], but uses the already detected saccades for segmenting the recordings into slow and fast phases, instead of finding the maxima and minima in the speed signal. An OKN is detected when the overall direction of gaze movement during an intersaccadic interval is roughly opposite (angle $\geq 90°$) to the direction of the adjacent saccades, whereas the two neighbouring saccades are roughly collinear (angle $\leq 70°$). In case of an already assigned VOR label, OKN+VOR is labelled instead.

6 RESULTS AND DISCUSSION

We publicly provide the entire collected eye tracking data set and its (partial) manual annotation, together with the video clips that were used as stimuli and the implementation of the annotation tool and the I-S^{5}T algorithm on the project page: https://web.gin.g-node.org/ioannis.agtzidis/360_em_dataset.

The collected hand-labelled data make it possible to examine in detail the eye movement patterns and typical behaviours that observers exhibit when viewing dynamic 360° content. The assigned primary eye movement labels consist of 74.9% fixations (4193 events), 10.5% saccades (3964 events), 9.9% SP (552 events), and 4.7% noise (553 events). The secondary eye movement labels include 28.0% VOR (1825 events), 15.9% of a combination of OKN+VOR (295 events), 0.8% OKN without VOR (21 events), and 1.4% head pursuit (52 events). We believe that this is the first data set that addresses the eye movement strategies in 360° video viewing for such a large spectrum of eye movement classes at the same time. Our data can serve as basis for further gaze behaviour analysis and gaze event detection algorithm testing.

6.1 Automatic Classification Quality

To evaluate the performance of our algorithmic event detection as well as to explain the benefits of utilising the data from both the eye and the head tracking, we compared the performance of our algorithmic detector I-S^{5}T against two versions of the same algorithm: one that only uses the speed of the eye within the head (e.g. directly applicable to mobile eye tracking data), the other – E+H gaze data (e.g. in HMD recordings, if additional data were discarded) instead of a combination of all available movement readouts. We split our ground truth data into a training and a test set, each containing one manually annotated eye tracking recording for each video. The sets of recorded participants in training and test sets do not intersect. For all algorithm versions, we selected the gaze speed thresholds (i.e. head speed threshold was not optimised) with a similar grid-search optimisation procedure on the training set – first, the two thresholds for saccade detection were jointly optimised, then the remaining two gaze speed thresholds.

We refer to the algorithm versions as (i) *combined* for the "main" proposed version – the I-S^5T algorithm – that used both the eye-in-head and eye-in-world speeds, as well as head speed for threshold scaling, (ii) *FOV* for the version that used the eye-in-head gaze speed only, and (iii) *E+H* for the one that only used the eye-in-world speeds. Of course, the FOV and E+H versions did not detect the combinations of head and eye movements, so the secondary labels of VOR and head pursuit are not assigned. OKN detection is possible, however. Since there was much more OKN+VOR than pure OKN in our data, whenever OKN was detected based on the FOV or E+H algorithm versions, an OKN+VOR label was assigned.

We evaluated all three algorithm versions on the manually labelled test set. Table 3 contains the sample- and event-level evaluation measures (in the form of F1 scores) for our approaches. Event-level evaluation follows the procedure of [Hooge et al. 2017].

All three algorithms achieve relatively high F1 scores for fixation and saccade detection, with the FOV version yielding substantially lower scores. This indicates that saccades can be easily confused with the eyes compensating for the head movement. The difference is even more pronounced for SP detection, with the FOV version of the algorithm lagging far behind. The differences between the E+H version and the "combined" versions are generally very small for the primary eye movement classes (fixations, saccades, SP, and noise), with the combined variant achieving marginally higher scores. For the secondary labels, only the version that combined eye-in-head and eye-in-world speeds was able to detect the full spectrum of the defined eye movements, as most of the secondary labels require the knowledge of both the eye and the head movement information. OKN detection was comparable across the board.

Our evaluation has demonstrated that eye movement classification algorithms could benefit from using all the available information about head and gaze in every frame of reference. This is especially important for distinguishing eye movements driven by the retinal input (e.g. smooth pursuit) and other sensory intakes (e.g. VOR), which is supported by the definitions of the eye movements that we introduced in Section 4.1. Those necessarily entail that using either eye-in-head or eye-in-world coordinate systems exclusively does not allow distinguishing even all the primary eye movements from one another: E.g. to differentiate between fixation + VOR and SP, the eye-in-world speeds are required; to discriminate between fixation + head pursuit and SP labels, however, the eye-in-head coordinates are critical. These observations are particularly relevant for wearable eye tracker scenarios, as gaze coordinates are often reported in the FOV only, which corresponds to the worst-performing version of our algorithm (despite parameter optimisation). In this set-up, additional classification power can be gained by incorporating head motion information, e.g. from a gyroscope [Hossain and Miléus 2016] or from the field camera images [Kinsman et al. 2012].

In general, using fixed thresholds (despite their scaling with gaze speed, as in I-S^5T) is not as flexible as the adaptive thresholds human annotators implicitly use, which depend on the noise level, for example. Experts also take into account a much larger context of gaze movement for each decision (compared to 100 ms windows in our approach). Expanding the analysis context for the algorithms also results in improved performance [Startsev et al. 2018]. Additionally, the eye movements' correspondence to the motion of the video objects is ignored by our algorithm, but is essential for accurately detecting tracking eye movements (and readily available to human annotators). The labels of our algorithm could be further refined using object tracking techniques or performing gaze target similarity analysis as in [Steil et al. 2018].

7 CONCLUSIONS

In this paper, we aimed to provide a starting point for comprehensive eye movement classification in an unrestrained head setting. To this end, we selected a very generic stimulus domain (naturalistic 360° video), where we can, however, retain auxiliary information such as precise head rotation. We collected a data set of eye tracking recordings for thirteen observers and manually annotated a representative part of it. We also presented a simple rule-based eye movement classification algorithm, which we optimised and tested in different settings, arguing that utilising both eye-in-head and eye-in-world statistics is necessary for the correct identification of eye movement classes. To the best of our knowledge, this is the first attempt to fully label the eye movement types with freely moving head in an immersive 360° paradigm. This data set and algorithm may serve as a basis to further improve both the theoretical and the practical foundations of eye movement detection in the real world.

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