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▶ To cite this version:

Sarah Goodwin, Arnaud Prouzeau, Ryan Whitelock-Jones, Christophe Hurter, Lee Lawrence, et al.. VETA: Visual eye-tracking analytics for the exploration of gaze patterns and behaviours. Visual Informatics, 2022, 6 (2), pp.1-13. 10.1016/j.visinf.2022.02.004. hal-03673359

HAL Id: hal-03673359 https://enac.hal.science/hal-03673359

Submitted on 22 Jul 2024

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VETA: Visual Eye-Tracking Analytics for the Exploration of Gaze Patterns and Behaviours

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Abstract

Eye tracking is growing in popularity for multiple application areas, yet analysing and exploring the large volume of complex data remains difficult for most users. We present a comprehensive eye tracking visual analytics system to enable the exploration and presentation of eye-tracking data across time and space in an efficient manner. The application allows the user to gain an overview of general patterns and perform deep visual analysis of local gaze exploration. The ability to link directly to the video of the underlying scene allows the visualisation insights to be verified on the fly. The system was motivated by the need to analyse eye-tracking data collected from an 'in the wild' study with energy network operators and has been further evaluated via interviews with 14 eye-tracking experts in multiple domains. Results suggest that, thanks to state-of-the-art visualisation techniques and by providing context with videos, our system could enable an improved analysis of eye-tracking data through interactive exploration, facilitating comparison between different participants or conditions, thus enhancing the presentation of complex data analysis to non-experts. This research paper provides four contributions: 1) analysis of a motivational use case demonstrating the need for rich visual-analytics workflow tools for eye-tracking data; 2) a highly dynamic system to visually explore and present complex eye-tracking

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Preprint submitted to Journal of LATEX Templates

January 22, 2022

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data; 3) insights from our our applied use case evaluation and interviews with experienced users demonstrating the potential for the system and visual analytics for the wider eye-tracking community; and 4) a set of informed design recommendations for visual eye-tracking analysis.

Keywords: Eye Tracking, Visual Analytics, Spatial-temporal Visualisation

1. Introduction

Eye tracking is widely used in various domains. For instance, in marketing it can be used to understand which advertisement is more attractive [1] or in human factors research, it can be used to understand how pilots react when a critical event occurs [2]. Eye-tracking data consists of a record over time of eye position relative to the scene being viewed. Important features relate to fixations (steady gaze on a particular location for some period of time) and saccades (quick eye movements between locations). Most eye tracking occurs in controlled studies in laboratories that require external sensors to track gaze. However, with the growing development of wearable eye trackers, it is now possible to perform 'in the wild' studies (i.e. in the participant's natural environment) by having participants wear glasses [3].

These 'in the wild' studies tend to be longer, producing more data, but also more noise as they are less controlled than studies in laboratories. In this type of study, we particularly focus on situations in which users have a complex workspace (i.e. more than one screen) but in which they are static most of the time (although rotation can be considered), like a control room or an aircraft cockpit. We, however, do not consider context in which users are moving, like someone playing tennis or a shopper moving in a supermarket (In this latter example, a participant looking at a specific shelf, and thus static in front of it could be considered). Current eye-tracking analysis tools provide limited solutions for the exploratory analysis and visualisation of such 'wild' data (e.g. Section 6.3.1). While standard software such as Tobii PRO Lab allows visualisation of gaze trajectories over time such software lacks the kind of holistic

visual workflow supporting all aspects of the exploratory sensemaking loop, from foraging through data, searching for evidence or schematising of knowledge to high-level sensemaking.

Motivated by an observational study in which we collected control-room operators' gaze data while they perform their actual tasks, we present Visual Eye-Tracking Analytics (VETA), a system to visually explore and analyse eyetracking data including, but not limited to, wearable eye tracking devices. This combines a number of distinct visual analytical features through a novel perspective of using eye-tracking data through spatial and temporal linked views, together with an immediate link between the data and the eye-tracking video, to allow for video-driven analytics (see Section 4). It provides clutter reduction to highlight general patterns in the data, by using techniques such as interactive lenses [4] and edge bundling [5]. It extends typical eye-tracking analysis by allowing users to define and manipulate dynamic Areas Of Interest (AOI) and Time Windows of Interest (TWI). We also propose the predefined classification of saccades: 'glance' and 'short distance saccades' which were found to be highly distinguishable and beneficial to filter and explore separately in our analysis. Finally, small multiple comparisons, annotation and the possibility to save and share the state of the analysis, allow for exploration, collaboration and sensemaking.

We assess the functionality of VETA, first, by demonstrating how we used the system to find new insights from our motivational use case with energy network operators (see Section 5). Then we discuss the results of interviews with 14 experienced eye-tracking users from different domains providing a richer understanding of the potential for the system to the wider community (see Section 6).

Results suggest that the interactive functionality, such as dynamic AOIs, linked spatial and temporal views, and the classification of saccades, would improve their exploration of eye tracking data. Other functionality, such as side-by-side comparison and the save mechanism, are also important to understand what are the common gaze patterns and the difference in behaviour between the participants or conditions in a study. Finally, the use of annotation and simple but

informative visualisations of spatial, directional and time-based gaze patterns allow analytical insights from complex eye-tracking data to be understood by non-expert users. From our evaluation of the software we propose a set of design guidelines for future work in visual exploratory analysis of eye tracking data (see Section 7).

This paper enriches the growing body of knowledge for eye-tracking visualisation and analytics, with four specific contributions:

- (1) analysis of a use case of 'wild' data collected from a real-world control room environment motivating the need for a tool supporting rich visual-analytics workflow for eye-tracking data;
- (2) the design and implementation of a **comprehensive and highly dynamic** system to visually explore and present complex eye-tracking data;
- (3) **rich and detailed insights** from our applied use case and from interviews with experienced eye-tracking analysts demonstrating the benefits and future potential for the system;
- (4) a set of **informed design guidelines** for exploratory visual analysis of complex eye-tracking data;

2. Motivational Use Case: Network Control Room

The design of VETA was motivated by the need for an efficient and interactive tool to analyse eye tracking data from a study¹ measuring the activities of operators in the Australian national energy network control room. Because of the complexity and duration of such activities, the data coming from such studies often contains noise and are hard to classify, and thus, difficult to handle using existing commercial analysis software (e.g. Tobii Pro Lab²).

80 2.1. Network Control Room Use Case

¹The study itself is not the focus of this paper, but it provides a valuable use case of a study 'in the wild' with a large amount of eye tracking data.

²https://www.tobiipro.com/product-listing/tobii-pro-lab/

In the control room there are 2-3 operators at any time, each of them has a workstation which is composed of 7 screens on two rows (see Fig. 4). The screens present numerous software applications simultaneously and the operators are able to organise these applications on any of their screens in a way that they believe maximises their understanding and interaction between those applications. As part of the study we recorded the gaze of the operator using a wearable eye tracker (Tobii Pro Glasses 2³). These wearable eye trackers have outward facing cameras that record video of what the operator was looking at, i.e. on their screens or any other elements of the environment. As per Tobii instructions, these were calibrated to 60 centimetres, which is similar to the distance that the operators typically sit away from the screens. They tend to work facing the screens most of the time.

The study was designed to provide quantitative data to allow us to derive insights and recommendations for improvements to the control systems and the operators' workspace. More precisely, we expected to use the eye tracking data to achieve four outcomes.

Outcome 11) To better comprehend the actions of operators during both routine activities and in response to exceptional events. In these contexts eye-tracking data allows us to understand operators' varying attention to different parts of the display over an extended time, such as operators having to transition repetitively between two applications that can be physically far from each other on the (large tiled-display) workspace. Notably, given the size of the screens, this can involve movement of the head in tandem with the eyes. For this work we are interested primarily in attention and therefore do not explore head and eye movement separately, however the techniques we describe could be extended to provide this separation, for example, to investigate visual field bias, i.e. issues of central versus peripheral vision. Whilst visual field biases can occur in these contexts where it is harder to attend to certain sections of their peripheral vision, given the operators have undergone prior training (albeit at different

³https://www.tobiipro.com/product-listing/tobii-pro-glasses-2/

levels) and they organised the applications along their preferences, therefore we assume that the levels of visual field biases are minimal.

Outcome 22) To identify areas of the workspace that are rarely utilised versus locations for common activities e.g. during this period operators never looked at this application, which is positioned in one of the main screens.

Outcome 33) To compare the operators' reaction with the documented procedure, e.g. after this alarm, the operator did check this information.

Outcome 44) To understand gaze behaviour of experienced verses novice operators, e.g. novice operators spend more time scanning the network map to find a specific location, or spend

One specificity of the control room setup is the operators' workspace (i.e. 7 screens that can be considered as a single 3m×1m surface). Its large size makes visual search harder, and some visual behaviours can have a bigger impact on operators' performance compared to regular desktop screens. Glances (As defined by the ISO Norm 15007-1:2014, a glance is a quick look at an area of interest that may be comprised of more than one fixation and saccades to and from it [6]. It duration is between 500 ms and 3 s)(i.e. performing a quick visual back and forth to another place of the workspace) between two applications, for instance, can take more time, cause divided attention and lead to errors. Short saccades are also important as they can indicate a period in which the operator is focused on a specific application, and can therefore lead to inattention to activity happening in another part of the workspace. Being able to identify, isolate and analyse such specific gaze behaviours is important.

Whilst all operators involved in this control room study use the same applications and do similar tasks, each operator sets out their own workspace and their daily tasks are focused on different regions of the entire network, some being larger than others. Operator tasks also depend heavily on the state of the network. The network is usually divided in sub-regions on which one operator focuses. However, in the case of an unexpected event, operators regroup to collaboratively elaborate an appropriate response. Directly comparing between operator's gaze behaviour is not possible without understanding the wider context.

AOIs for one participant are different from another, and can totally depend on

the applications used and their location on the workspace. Whilst applications tend to stay in one place when they are open, they can be resized and new application windows may be opened to do a particular task. Through our analysis we found that although types of operator task may be determined by patterns of gaze and behaviour, operators' tasks need to be analysed individually. Identifying whether specific data patterns related to a particular task needed to be verified using the eye tracking video to determine which application was open on that operator's screen at the time of recording.

— 2.2. Exploratory Data Analysis

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As our study was performed 'in the wild' (i.e. in the control room while operators were performing real-time monitoring of the network), we could not control the content of the study. Operators' activities depended on the real-time situation and their habits. Thus, collected data is rather unstructured and noisy, and cannot be analysed with predefined assumptions about what task the operator is performing at the time. Initial visual exploration of the dataset is required to identify AOIs and TWIs containing interesting activity, before

Pirolli and Card divided the process of exploratory data analysis in two main loops [7]: (1) the foraging loop, in which the user actively seeks information, by searching and filtering the data, and (2) the sensemaking loop, in which the user extract pieces of knowledge from the data and understand the connections between them.

comparative or summative analysis can be performed.

In each of these loops, visualisation plays an important part. In the foraging loop, it can allow for visual filtering and highlighting, but also for visual aggregation of similar data in order to highlight outliers, this helps the user to extract the relevant data points [8]. In Jigsaw [9], Stasko et al. proposed to use connected views to interactively highlight the connection between the different data point and their dimensions.

In the sensemaking loop, visualisation allows the user to offload information from their working memory, by, for instance, allowing annotations and manual selection of information. To facilitate this offloading, but also support collaboration, Dunne et al. proposed to save intermediate state of the analysis and expose the exploration process using a graph [10].

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The overall workflow envisaged by Pirolli and Card links the foraging and sensemaking loops with a cycle of schematizing and search for evidence, as summarised in Fig. ??. Schematizing clevates observations from the foraging stage to knowledge ready for sensemaking, while search for evidence occurs when the analyst returns to foraging to assist further knowledge discovery. We broadly classify analysis activity for 'in the wild' eye-tracking data into these four main sets of activity within the Pirolli and Card sensemaking loop, which for brevity in our later analysis we label FOR, SCH, EVI, and SEN, as follows:

FORaging: Analysts need to be able to filter and aggregate data interactively. Each session in our study created a large amount of eye tracking data. In order to understand patterns and structure in the gaze trajectories—but also to highlight outliers—it is important to be able to visually filter and aggregate them [8].

SCHematizing and Search for EVIdence: analysts need to be able to flexibly encode activity to highlight and organise patterns (SCHematizing), and interpret them in the context of the original activity (search for EVIdence), for example, through viewing the patterns against the original video footage of the analyst's point of view [7].

SENsemaking: When dealing with a large quantity of data, analysts' working memory relating visual patterns (or evidence) to insights (validated hypotheses), can quickly become overloaded [7]. Annotation can be used to offload this working memory directly to the visualisation. As analysis is detailed, takes time and needs to be reproducible it is important to be able to save the state of analysis including the encoding and analyst's notes. It is also important to be able to easily share between collaborators in order for other members of the team to observe and comprehend the steps of analysis that have been performed and interpret the patterns with their own knowledge [10].

3. Related Work

In this section we report on previous work that has inspired us to build our system. Although no single prior system provides the full set of features that we require nor the novel features we have developed, VETA takes advantages of existing gaze data visualisation and analytic tools and extends them with novel interactive features (e.g. interactive lenses, animations, bundling, small multiples).

In traditional eye-tracking analysis one would segment the session into predefined TWI, and define AOI in the workspace. Typical metrics include the time spent on each AOI during each TWI, or the number of transitions between AOIs. Current eye-tracking analysis software provides tools to define these TWIs and AOIs, as well as overview visualisations such as heatmaps and gaze plots. Our system is not based on the exploration of static AOIs, but on the combination of recorded video and dynamic Focus plus Context (F+C) techniques such as interactive lenses to leverage the user's ability to gain a better understanding of recorded gaze datasets. With complex and noisy data the context is fundamental in understanding the detail of locally investigated eye-tracking data. F+C techniques has previously been shown to reduce the noise and facilitate visual clustering of the data (e.g. MoleView [11])

Gaze data visualisation and analytic tools: Eye-tracking technology has a long history of capture and analysis of user gaze behaviours [12, 13]. Commercial solutions are available, covering the whole data processing pipeline, from data capture to cleaning, processing and presentation, including Tobii Lab ⁴, SMI be Gaze; Blickshift ⁵ and Eyevido ⁶. Open-source solutions exist such as Ogama [14] and Web-based solutions are also available [15]. These gaze data analytics tools collect a large body of records consisting of fixation points linked by paths. These tools can visualise and extract relevant user patterns

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⁴https://www.tobii.com/

⁵https://www.blickshift.com/

⁶https://eyevido.de/

Table 1: Summary table of systems providing both point-based and AOI-based visualisations of gaze data extracted from Blascheck et al. [26], with the addition of VETA. Note: The purpose of this table is not to show the complete classification, but only the dimension for which there differences between the systems.

	Gaze Data		Visualisation	
	Temporal	Spatial	Animated	Static
Stellmach et al. [27]	•	•	0	•
Weibel et al. [28]	•	0	•	•
Pfeiffer [29]	0	•	•	0
VETA	•	•	•	•

via heatmaps [16], scanpaths [17, 13], AOIs [18, 19], Sankey diagrams [20] or can automatically annotate interesting video sections [21]. Andrienko et al. used geographical visual analytics approaches to explore gaze data based on AOI [22]. Blasheck et al. investigated multiple source aggregation among eye tracking data and think-aloud to evaluate an interactive system [23]. Other systems use AOI and space-time cube data representations to investigate eye-tracking datasets [24, 25].

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Blascheck et al. proposed a classification of eye tracking visualisation systems in a recent survey [26]. They first classified the systems into *Point-based* and *AOI-based* visualisations, and only 3 systems propose both type of visualisations, which is also the case of VETA. Table 1 proposed a summary of Blascheck et al. classification for this three systems and we compare them with VETA. Stellmach et al. proposed a system to visualise both spatial and temporal gaze data for 3D Virtual Environnements [27]. The system provides an object-based visualisations of the gaze as well as a surface one (i.e. a heatmap) and a timeline indicating which object is in focus, all of this is static. In their system [28], Weibel et al. focused mostly on temporal data and visualise them using a timeline and scanpath that can be animated. Finally, Pfeiffer proposed animated techniques to visualise spatial and temporal gaze data in 3D environnements [29]. The author used both 3D heatmaps and 3D scanpaths to

represent the gaze data. Compared to these systems, VETA can manage both temporal and spatial data and uses both animated and static visualisations. The reason to propose a various panel of techniques is to allow users to choose the most appropriate to their data exploration. Compared to the large majority of these systems, our work does not focus on the use of static AOIs but on the combination of dynamic and interactive lenses together with the ability to switch to the recorded video to support the understanding and interpretations of the data.

Focus plus Context trajectoryflow analytic techniques: Heatmaps, scan-paths, transition matrices and charts of AOIs provide useful visualisation techniques to support insight discovery from gaze data. However, they always provide a trade-off between the visualisation of the raw data (often dense and complex) and a given level of abstraction which gives a specific point of view of the data. One possible solution to such limitations is to use Focus plus Context (F+C) techniques which show dual data visualisations at different levels of detail. F+C techniques emphasise specific areas [30] while showing contextual information. A survey across application domains is available which also investigates lens deformations [4].

Lense have been widely used as a focus+context technique, especially with graphs mostly to locally filter edges that can quickly clutter the visualisation. Lenses can act on two different elements, nodes or edges. Tominski et al. presented a lens of each type: one that brought neighboring nodes closer to the node inside the lens and one that remove all the non-local edges that went through it (a local edge is an edge linked to a node inside the lens) [31]. Most latter work tended to focus on edges as nodes position can encode data and thus represent information (which is the case for gaze trajectories). With Edgelens [32], Wong et al. proposed to curve the edges that went through the lens instead of removing them. The same concept is adapted to only non-local edges by Schmidt et al. [33]. In EdgeAnalyzer [34], Panagioditis et al. explored the use of multiple lenses in order to perform set operations (e.g. to filter the edges that went through two different lenses). The techniques also allow to fil-

ter inside the lens using different parameters including their direction and other non-geometrical data dimensions. Finally it allowed to bundle locally edges inside the lenses. Finally, with MultiLens, Kister et al. combine most of these different lens techniques in a customizable one [35].

Trajectories can be considered as a specific type of graph in which nodes represent waypoints and edges is the path interpolation between them. Early works on lenses for trajectories mostly focuses on 3D flows visualisations. Fuhrmann and Groller proposed a 3D lens which act as a cliping plane and show trajectories with a higher resolution when they are behind the lens [36]. Mattausch et al. proposed a similar solution with a 3D box as a lens [37]. In Flowolens [38], Gasteiger et al. do not filter trajectories with the lens, but change its encoding and add another data dimension locally that they consider as contextual information. In TrajectoryLenses [39], Krüger et al. took inspiration from EdgeAnalyzer and explore the use of several lenses to perform set operations on 2D trajectories. They allow the user to filter trajectories by origin, destination or waypoints, all of which defined using lenses. Their system also provide a timeline to visualise trajectories distribution by hours, days or months. Finally, Ferreira et al. presented RoseTrajVis [40], a techniques that provides a summary of the information about the trajectories that go through a lens instead of filtering. A colored rose diagram shows the distribution of direction of the trajectories and the average speed for each.

We took inspiration from most of these work on lenses in the design of our interactive AOIs and extend them by adapting them for gaze data. We explore, in this paper, the use of these interactive AOIs to perform complex filtering operation and show contextual information regarding users'gaze behaviour (including their use of glances), and its spatial and temporal distribution. In addition to interactive lenses, we use other techniques to help the exploration and the understanding of gaze dataset using, for instance, animated transition [41] and trajectories bundling [42].

VETA uses F+C to allow the user to investigate AOIs while keeping contextual information and showing gaze flow directions to indicate where the gaze comes

from and goes to. While trajectories lows can be visualised statically thanks to their characteristics: origin, destination, intensity and clusters [43], other techniques use animation—such as particle systems [44]—to show flow parameters. VETA extends known features with the combination of animation and interactive F+C techniques.

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Animation and view linking: Animated visualisations are common in data exploration [41] and they are attractive for data presentation and communication purposes [45]. For instance, animated transitions can aid the perception of changes of the underlying data [46, 47, 48, 11, 49] and thus they have been widely used for animated visualisation. Heer and Robertson [50] introduced a taxonomy of transition types and found that animated transitions can significantly improve graphical perception. As a global level, effective animations have to follow two principles: Congruence and Apprehension [51]. The former suggests that the animation must relate to the information to be conveyed, while the latter suggests that the animation should be easy to comprehend. VETA uses animation to ease transitioning between different visual mapping, which helps the user keep track of the data of interest. Such smooth transition can also operate to smoothly remove clutter in dense views thanks to visual simplification.

Visual simplification tools: Gaze datasets are often dense with many fixations and saccades, which can create visually cluttered views. Specific F+C techniques showing animated visual simplification [11] can help to partially address this, to make patterns in the data more visible. More generally with trajectory data, researchers explored how to use the third dimension to visualise individual trajectories at the same time as aggregated ones [52], and they also explored the use of interactive lenses to show details at specific locations [39]. This has been adapted for eye-tracking data in SaccadeLenses [53].

A class of techniques known as edge or trailset bundling can simplify the dense and complex data produced by eye-tracking systems, Lhuillier et al. [42] and Zhou et al. [54] provide a survey. A large range of algorithms exist to create such bundling of trailset data, beginning with an assumption of a hierarchical

data structure [55], to more recent, faster and more generally applicable scalable methods [56, 57, 42]. Recent advanced techniques capture the statistical properties of the visually aggregated bundles [58] or a patchwork of multiple technique aggregation [59]. Such techniques have also been applied to static visualisation of bundled set of user gaze when investigating junk charts [60]. VETA extends such technique with its usage for real-time edge bundling technique [61] to aid the user interpretation.

4. Design and Development

VETA provides a combination of exploratory visualisation and interaction capabilities to allow the user to gain a quick visual overview of the data as well as to explore user gaze behaviour in detail. This has been implemented in the following manner. A video showing the system functions and interactions accompanies can be found in our supplementary web link⁷.

4.1. Data Processing and Implementation

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Three kinds of data are utilised: (1) eye tracking data of a sequence of fixations, each containing time of recording, an X and Y coordinate in space, and a $\Delta time$ representing how long the subject fixated at that point. This data is stored as a CSV file, (2) a background image as spatial reference to give the user context and (3) a video of the subjects' actions can be attached from the original eye-tracker recording. The eye tracking data can be explored without the mapped image or the video, however these provide further context for understanding the behaviour and verifying patterns and insights.

Mapping gaze data onto a reference image of a real-world environment is an increasingly common technique included in eye tracking software. Tobii Pro and other eye-tracking providers allow for tracking data to be mapped onto a still image of the environment, and gaze data of computer screens will usually be calibrated to be recorded in terms of screen coordinates, while gaze data

⁷https://youtu.be/NsMP6eDtvgM

on a scrollable webpage might be given in page coordinates, accounting for scrolling. This can be done manually, or using image processing algorithms to find matching regions on the reference image [62].

The mapped gaze coordinates produced by the eye tracking software can then be formatted for importing into VETA. We used Tobii Pro Studio for the initial mapping of the data which is then exported to a CSV files which can be imported in the VETA application.

For the VETA application, we implemented the application in Processing 3.5.3⁸ for speed of data processing as well as flexibility of the graphical interface. The Processing Video library is used for accessing video files, the Java Swing library for file access and the Java OpenCL⁹ library for accessing GPU power for implementing real-time dynamic edge-bundling. It was developed and runs well on a standard computer. The code is open and available on GitHub¹⁰.

4.2. Interface Design

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Data is presented spatially on a *canvas* (i.e. the area of the workspace in which the gaze points are displayed) and temporally on the *timeline*.

The prototype includes controls for filtering and manipulating parameters of the data as well as a legend to distinguish colours and filter by colour. These features can be turned off and on, and also have keyboard shortcuts. Eyetracking events are shown spatially on the canvas on top of the image to which the data is mapped, as explained in Sec. 4.1. Eye-tracking events are also shown chronologically on the timeline beneath the canvas (e.g. see Fig.3-c). Each timeslice is presented as a vertical rectangle, where the width is proportional to the length of the recording divided by the screen width.

Interaction in the canvas—i.e. filtering data or changing the colour mode of presentation—are reflected in both the canvas and the timeline through linked views. Visible data can be filtered spatially by the creation of user-defined *lenses*

 $^{^8 \}mathrm{https://processing.org/}$

⁹http://www.jocl.org/

¹⁰https://github.com/rtwhi2/VETA

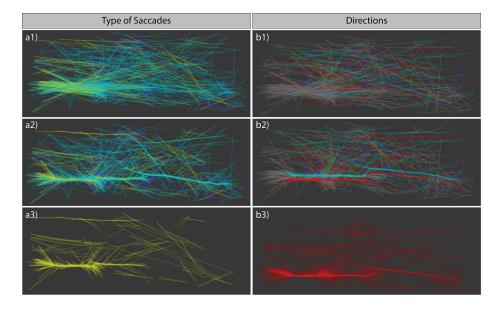


Figure 1: Filter and aggregation of saccades using type and directional colour modes a) by saccade type: short (blue), glance (yellow) and other (turquoise) and b) coloured by direction with 8 subclasses (refer to colour wheel in section 4.2.1. 1) all saccades, 2) bundling with colour mode, 3) bundling filtered by colour, a. all glances, b. all right saccades

defining AOIs on the canvas. Visible data can also be filtered via the timeline to a specific TWI using interactive range sliders. The user can zoom into this selected TWI. A horizontal line (e.g. see Fig.4-a2) divides the timeline. Above the line provides visual information about fixations (in each AOI). Below the line provides information about activate saccades. Filtered data is shown in grey. User defined AOIs are also presented on the timeline in horizontal rows to allow for exploration of AOI information over time (e.g. see Fig.4-a2). Finally, the user has the ability to switch between the data-exploration mode and the eye-tracking video at any time to verify their insights.

4.2.1. Visual Encoding and Clutter Reduction

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Immediately on top of the mapped image all fixations in the full dataset are displayed for *context*. This provides an overview of the activity to enable

natural clusters to be identified instantaneously. The user has the ability to turn this context layer on and off during their exploration process. These fixations are shown on the canvas as transparent circles (with 20% transparency). The appearance of the circles can be altered to present them either equally sized or sized proportionally to the length of the fixation. The maximum circle size can also be adjusted manually.

On top of the context layer, saccades between the fixations are presented as lines linking fixation locations on the canvas. We distinguish two specific subtypes of saccades that were identified during our design phase: Short-distance saccades and glances (Fig. 1-a). Glance is a common type of gaze pattern used to analyse users' behavior in different domain: piloting aicrafts [63], construction [64] and command and control contexts [65]. It can be used to differentiate between novice or expert users, to understand better their attention (and when it is misplaced or blurred), or to analyse and their performance for a specific task.

Short-distance saccades often represent the subject's eye moving within a small area (e.g. an AOI), rather than movement between components or to new locations [13]. The distribution of short saccades can therefore help highlight where natural AOIs supported by the data exist, yet they provide little information about the interaction between those AOIs. By default short saccades are defined as 100 pixels in length as this was determined as appropriate for our use case but the user has the ability to alter this value. If the minimal distance is reduced to zero no sub-selection takes place and all saccades are classed as other saccades.

A common pattern observed was a *glance*, where the subject fixates in one area, then moves to fixate in another and then immediately moves back to near where they were fixating immediately before. If the subject repeatedly moves back and forth between two components, without looking anywhere else, these are considered as *glance* saccades. We found that this pattern is fairly common in our data and provides distinct information about the relationship between components. For example, subjects might *glance* to a component that holds

information necessary for a task in another component, or that might contain an alarm message that needs to be checked regularly. Since these two types give different information from other saccades, it is possible to filter them separately.

Saccades can be filtered by type. Type is also distinguished through the use of colour: short (blue), glance (yellow) and other (turquoise). Apart from these default colours for saccades, further colour modes allow for more in-depth exploration. To allow for directional gaze patterns to be explored, a directional colour schema is provided. A colour wheel is divided into 8 classes, to allow for visual clustering of saccades by general direction of eye movement. Using this schema, horizontal and vertical movement in different directions can be visually distinguished by colour, as shown in Fig. 1-b, where red indicates the right saccades and turquoise the left ones, etc.

Direction of saccades can also be presented using animation, where fireflies animate along the saccade rather than shown as a solid line. Finally, a custom colour schema provides the ability for the user to define their own categories (using an additional column in the input file). This custom mode could be used for common tasks or TWIs for instance.

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To allow for overarching patterns to be observed in the saccade trajectories even when significant amounts of data are visible, dynamic force-directed edge bundling can be performed on the fly [61] (Fig. 1-a2/b2). This is applied on the saccades that are currently visible for instance on all saccades, those in a certain TWI or those within a particular AOI. Bundling is also effected by the colour schema: if colour is by type, the glance and normal saccades will bundle separately, and if by direction, lane-forming directional edge-bundling is used so that the weight of transitions in each direction can be compared. The degree of rigidity in the saccades being bundled can be controlled by the K parameter through the interface. Bundling can be reset at anytime. Fig. 1-a2 shows how bundling linked with the colour mode can help to remove saccade clutter. More specifically, Fig.1-b2 demonstrates that directional edge-bundling can be used to help identify user behaviour patterns in the data visually. By clicking on one colour in the legend, it is possible to show only the saccades of that colour

(Fig 1-a/b3).

4.2.2. Exploring Areas of Interest

Areas of interest (AOI) are defined by the creation of interactive lenses that can be manipulated manually using the mouse. The user has the ability to create, reshape, select or delete them. They are shaped as superellipses, ranging from diamonds to rectangles, where the user has the flexibility to control the size, shape and aspect ratio. In each AOI the percentage of the fixation duration is displayed as percentage value. As this is moved around the screen, this value recalculates on the fly.

Gaze datasets are often dense with many fixations and saccades, which can create visually cluttered views. The use of interactive lenses in for eye tracking have shown to be promising [53]. AOI can be used to reduce data clutter and filter the data for exploration in several ways. Using AOI saccades can be filtered using multiple filter modes: within an AOI, around an AOI, from/to one AOI or between multiple AOIs. AOIs can also be used to remove fixations shown on the canvas to remove outliers or unnecessary data. Fixations can be removed from view using two options: within or outside an AOI. This action can be reset at anytime to return to the full dataset.

All fixations within an AOI are highlighted on the canvas using white opaque circles. These are 30% of the size of the context circles shown in the background. This allows the user to identify visual clusters within the AOI easily, alleviating issues of occlusion due to overlapping fixations. Background context fixations can be turned off or on to aid comprehension and exploration at this time.

When an AOI is activated the interactions between the AOI and surrounding space are highlighted in the foreground. Selected fixations outside the AOI are shown with 80% transparency, where three types of fixation are distinguished through the use of colour; Fixations which occurred shortly before a visit (maroon), fixations shortly after (green), and fixations representing a glance both in and out of the AOI (where the subjects attention moves from the AOI, to the location and back to a location within the AOI) (yellow), as shown in Fig. 2.

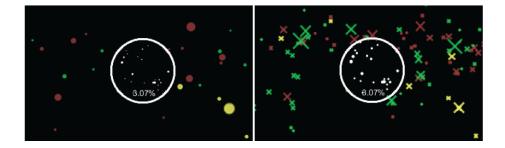


Figure 2: Left: the generic view provides the fixation before and after each fixation inside the AOI. Right: the alternate view provides all the fixations in a chosen amount of time before and after each fixation inside the AOI (in this example, the chosen amount of time is 5 seconds).

Two different interpretations of 'shortly before' are applied. In the *generic view*, the immediate sequence of fixations is used, with only a fixation immediately before or after a fixation within the AOI being marked (Fig. 2-left). In the *alternative view*, a user-controlled window of time is provided, where all fixations within a given number of seconds before or after a fixation within the AOI are highlighted (Fig. 2-right). To quickly distinguish between these two modes a circle is used to present fixations in the generic view, whilst a cross is used in the alternative view.

Each AOI is identifiable in the timeline, allowing the user to see AOI selections over time. The fixation section of the timeline, above the horizontal line, is split by the number of AOIs on the screen. These appear in order of creation. The selected AOI is highlighted, and the selected filter and colour modes are reflected both in the canvas and timeline. To allow for quick exploration of selected data over time, hovering the mouse over a fixation activates a line connecting the fixation to the timeline. To provide a visual overview of the distribution of transitions the selected fixations can be presented spatially, by direction or by time. The "by direction" mode maps the surrounding fixations around the AOI perimeter (Fig. 3-b and Fig. 4), whilst "by time" maps the surrounding fixations chronologically along the timeline (Fig. 3-c). These histogram views are implemented using animated transitions to allow the fixation

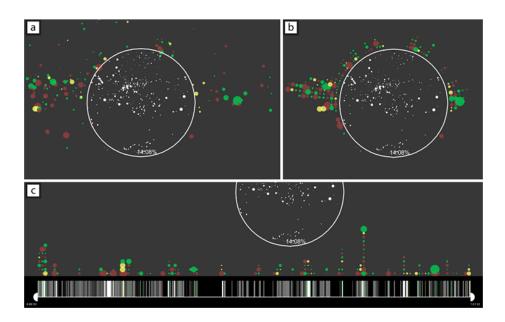


Figure 3: Circular AOI presenting fixations within the AOI in white and selected fixations outside the AOI in three colours: Shortly before (maroon), shortly after (green) and *glances*, both out then in again (yellow). These surrounding fixations sized by duration of fixation time can be presented (a) spatially, (b) by direction or (c) by time (where the white bars indicate a fixation at that time).

locations to be visually followed, as shown in the accompanying video. Such animated transitions have been shown to aid the perception of changes of the underlying data [46, 47, 48, 11, 49].

To allow scan paths of the subjects' attention to be explored. A travel-line can be drawn between the 'before' fixation and the matching 'after' fixation. In the alternative view, where multiple before and after fixations can exist for each visit to the AOI, the entire saccade trajectory, within the window of time around a visit to the AOI defined by the user, can be drawn. This allows scan paths to be investigated, however, large AOIs or TWIs may lead to the view being overly cluttered.

4.2.3. Provenance and Sense-making

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In order to ensure the system is useful in practice we have incorporated a number of features to aid dataset comparison, user collaboration and report making. VETA provides the ability for users to explore multiple datasets in one view in juxtaposition. The screen can be divided into four small-multiple sections, and each small multiple can present subsets of the same dataset (i.e. different AOIs or TWIs) or different datasets (i.e. different participants). Selection and filtering within each small multiple can be manipulated separately or they can be explored all together. The user has the ability to zoom into one view for exploration and move back to the multi-view easily. At present VETA is limited to four juxtaposed small-multiple views but this could be extended if necessary and if system resources allow.

The user has the ability to load different datasets and to save workspace settings, this includes all selections and filtering, including AOI, TWI, bundling and colour mode settings. Saved workspaces can be loaded into VETA at anytime and when saved or loaded they appear as a sequence of small thumbnails on the right side of the screen. This allows for a smooth exploration process being able to move between workspaces quickly. In addition to saving settings record making is essential in the data exploration process. VETA allows user-defined text notes to be created at any time, anywhere on the canvas or linked to the

timeline. These notes appear as the top layer and can be edited or deleted at anytime. This not only allows the provenance of the exploration process to be recorded but allows for collaboration with others. Finally, the workspace can be saved by the user at anytime.

5. Use Case: Analysis of a Network Control Room

In the context of the study presented in Section 2 we recorded gaze (using a wearable eye tracker) of a network operator during the first hour of their shift, termed as the handover session between the night and day shift, on two consecutive days. During the handover, the night shift operator gives a summary to the day shift operator (our participant) of what happened during the night and of what is expected to happen during the day. The day shift operator then sets up their workspace and starts working. It is important to note that Day 1 of the study was the first day of the day shift cycle of our participant, which means they had just had 5 days off and therefore had limited situational awareness of the network. We used VETA to compare the gaze between these two sessions to assess the impact of this lack of situational awareness on operators activities. For this analysis we refer to each screen as Screens 1-7 as shown in (Fig. 4a1). For each action, we give in parenthesis the functionality we used from the system and which step from the sensemaking loop it is. In the last subsection, the comparison, we link our findings with the outcomes from Section 2. Each session lasted around 1 hour and we have around 2500 fixations in each, which represent almost one fixation per second. On the first day, there were 326 transitions between two screens, which is 5.4 transitions per minute. On the second day, there were 256 transitions between two screens, which represents 4.2 transitions per minute.

5.1. Analysis of Day 1

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Using VETA, we loaded the mapped data with the appropriate background image. We started by displaying only the short saccades (Saccades filtering—

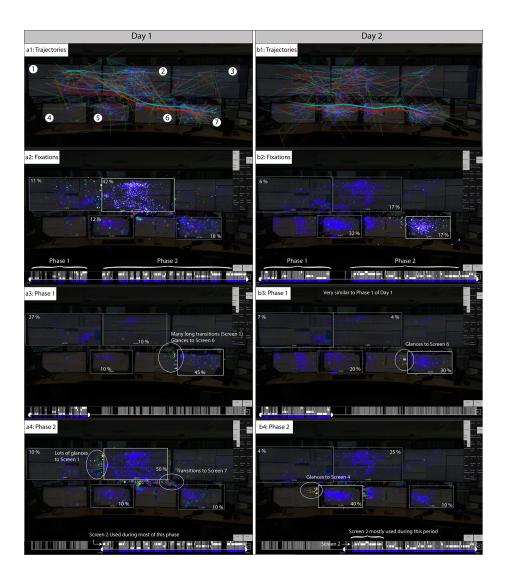


Figure 4: Comparison of the handover session on Day 1 (column a) and 2 (column b) for the same operator. (a-b1) Directional bundling of all saccades for both sessions. (a-b2) Fixations (green, yellow, maroon) and short saccades (blue) with 4 AOIs for both sessions. (a-b3) Fixations and short saccades with 4 AOIs for the Phase 1. (a-b4) Fixations and short saccades with 4 AOIs for both sessions. (a-b3) Fixations and short saccades with 4 AOIs for the Phase 2. Annotations have been added for descriptive purpose and enlarged for readability.

FOR), to see which area of the workspace the participant focused on the most (Fig. 4-a2). We could see that the participant mostly focused on 4 screens during the session (see Fig. 4-a1 for screen number). We then created an interactive AOI for each screen to get a more accurate idea of relative time spent across screens: Screen 2 (42%), Screen 7 (18%), Screen 5 (12%), and Screen 1 (11%) (Interactive AOIs—FOR). By looking at the timeline, we saw a 5 minute period during which no data was recorded. By looking at the video, we can easily see that the participant took a coffee break during this pause (Video exploration—EVI). Considering the evident difference in screen focus between these times we decided to divide the session into two phases for analysis: Phase 1 before and Phase 2 after the break.

We focused first on Phase 1, and thus adjust the slider on the timeline to only display gaze data during this period (Fig. 4-a3) (Time filtering—SEN). The AOIs gave us the percentage of screen usage. In this phase, the participant was 45% focused on Screen 7, 27% on Screen 1, and around 10% on Screens 2 and 5. We then displayed the long saccades and filtered the ones which were not between the AOIs (Saccades filtering—FOR). We observed very few transitions between the different screens. This is confirmed by visualising the fixations sequentially (i.e. using the colour codes differentiating before/after/glance, as shown in Fig. 3) for each AOI (Before/After glances—SCH). This allowed us to also notice that the participant glanced a few times at the Screen 6 while working on Screen 7. A look at the timeline confirms that during this period, the participant focused on each of the 4 screens for long periods of time, which therefore reduce the need to transition between them. A look at the video showed us that the participant was actually setting up the different applications during this time (Video exploration—EVI). They had to open and prepare around 15 applications, which explains the long periods of time spent on each screen. This process was mostly managed from Screen 7 on which the applications were initially opened.

Keeping the same AOIs, we then adjusted the timeline to Phase 2 (Fig. 4-a4) (Time filtering—SEN). The screen usage radically changed: Screen 2 is

used around 50% of the total time, while screens 1, 5, and 7 are each used for around 10% of the time. When looking at the transitions (Saccades filtering —FOR), they mostly happened between Screen 2 and screens 1 and 7. By activating the directional histogram around the AOI on Screen 2, we can see that more than half of the transitions with Screen 1 are glances (Histogram view —EVI). Checking the video allowed us to see that the participant had the real-time network diagram and the alarm summary applications on Screen 2 (Video exploration—EVI). We assume they are using this screen to gain an awareness of what happened before their shift (e.g. previous alarms, part of the network under maintenance), which is one of the main goals of the handover session. This required the participant to glance at Screen 1 to get additional information about the different events that happen in the previous days. Transition to Screen 7 to look at a geographical map with natural risk information (e.g. lightning, fire etc) on the monitored sector took more time than a simple glance.

5.2. Analysis of Day 2

We then loaded the data of the second day of recording and mapped this to the same background image, as the participant arranged their workspace in very similar ways on both days (Fig. 4-b2). When looking at the timeline, we can see there is a break similar to day 1 after the first 15 minutes. A quick look at the video showed us that again the participant took a coffee break (Video exploration—EVI). The overview of the short saccades seemed to be slightly different than in day 1 (Saccades filtering—SCH). We placed the same AOIs and observed different focus time proportion: the participant spent around 32% of the total time on Screen 5, 17% on both Screen 2 and 7 and only 6% on Screen 1 (Interactive AOIs—EVI).

We focused the timeline on Phase 1 (before the break), and observed a pattern similar to the previous day (Fig. 4-b3) (Time filtering—SEN). The participant spent 30% of the time on Screen 7, with several glances to Screen 6, 20% to Screen 5, 7% to Screen 1 and 4% to Screen 2. By briefly looking at the video, we could see that the activity was very similar to the previous day

(Video exploration—**EVI**). The participant set up their workspace during this phase.

Most of the difference with the previous day happened in Phase 2. Instead of mostly focused on Screen 2, the participant spent 40% of the time on Screen 5, and only 25% on Screen 2. They focused on Screen 7 10% of the time and Screen 1 4% (Fig. 4-b4). Interestingly, when looking at the timeline, we could see that most of the time they spent on Screen 2 happened in the beginning of the Phase 2, with glances to Screen 1. The video helped us confirm that their activity was similar to the day before (Video exploration—EVI), they were gaining an awareness of events that had happened prior to their shift. The rest of the phase is spent mostly on Screen 5. On this screen, the participant had placed mostly typical 'office' applications, such as their e-mail client and web browser. Checking the video showed us that during the rest of the phase, it was a quiet period for real-time operation tasks and therefore the participant was mostly occupied (with some exceptions) with e-mails, research for longer-term projects and other long-term planning tasks. Tasks expected during quiet periods of normal operation.

5.3. Comparison

The participant is expected to do the same tasks in both handover sessions. We could see a similar overall pattern in time management: after a verbal handover with the night operator, the participant started by setting up their workspace and then took a quick break prior to starting their daily tasks. However, the gaze trajectory tells a different story (Following Outcome 3). This is highlighted by a side-by-side comparison of the trajectories of both sessions aggregated using directional bundling (Fig. 4-a1 & b1) (Interactive bundling—SEN). We can observe that on Day 1, there is a clearly visible trajectory from Screen 1, to 2 and on to 5 and 7. On Day 2 the main branch of the trajectory goes from Screen 6 to Screen 7(Following Outcome 1). There is a small one from Screen 1 to 2, but less distinct than on Day 1 (Following Outcome 3). Analysis of the monitoring of the control room sessions in the afternoons of both

days, with the same participant, showed us a very similar trajectory pattern to the latter stage of Phase 2 of the handover session on Day 2.

The reasons for the difference between the two sessions lies in the fact that the participant is coming back from the required 5 days break in their shift cycle. On the first day, they need to gain a far greater awareness of what happened in the last few days and what was anticipated to occur in the next few days. By contrast, on Day 2, they only need to get an awareness of what happened over night. As the night had been relatively quiet and nothing unexpected had occurred, this takes only a short amount of time at the beginning of Phase 2. During the rest of this session they undertook the regular work that is expected during 'uneventful' network monitoring times (similar to what we observed in the afternoon sessions, as part of the wider study). Interestingly, the handover session on Day 1 seemed to leave a more positive imprint on the participant (as shown in the survey data), likely this is because they had had a break and the handover was more out of the ordinary than the subsequent day. Using the annotation functionalities, we added these insights directly overlaying the data, similar to what has been done in Fig. 4 (Annotation—SEN).

685 6. Experts' Feedback

To evaluate our system and gather feedback from other eye-tracking data analysts, we ran 14 individual feedback sessions. Participants were all eye tracking data users (i.e. they had used eye tracking data for their own work) with different levels of expertise. All participants did one session. This study was approved by Monash University Human Research Ethics Committee (Project 23671). The purpose of the session was to show the functionalities of the tool with our dataset, understand the activities of the participant and get their feedback about the tool itself.

6.1. Procedure

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All the sessions were performed remotely (due to COVID-19 restrictions) using video conference software. The first stage of the session started with a

brief introduction of the purpose of the tool and the study. Then, participants introduced themselves, their main activities, and how they use eye tracking (i.e. for what goal, which software tools they used, etc.). In the second stage of the interview we showed a video of the functionality of VETA, pausing when necessary. Finally, the third stage consisted of a discussion around the different ways such a tool could help them analyse their own data. One experimenter shared their screen with the tool running to answer specific questions regarding any functionalities or demonstrate specific processes. In this session, we used data from the use case presented in Sections 2 and 5. A session lasted roughly one hour and was audio and video recorded. After the session an online questionnaire was sent to the participants. This consisted of questions about the specific tools they use in their analysis and to gather post-interview feedback, allowing the participant some time to reflect.

710 6.2. Participants

We recruited 14 participants (Table 2 for details about their occupation and type of studies done with eye trackers), 11 males and 3 females, 2 aged between 18 and 24, 6 between 25 and 34, 4 between 35 and 44, 1 between 45 and 54, and 1 over 65. 4 participants declared using eye tracking data at least once a week, 4 at least once a month and 3 just once a year. 6 out of 14 participants mostly used eye tracking data in controlled experiments as a measure to perform comparisons, for instance to compare graph visualisations (P2), or to test different interfaces (P4). 9 out of 14 mostly used it in more observational studies of, for instance, students following a class (P5) or air force pilots training (P7). The analysis took between days for some participants (5/14), to several weeks (4/14) or months (2/14) for others.

6.3. Reflections

During our interviews, participants explained how they currently use eye tracking data, gave feedback on the tools and how it could adapt to their own use case. Overall, all participants found it could be useful for their analysis to

Table 2: Expertise of the 14 participants of the expert feedback sessions and the types of studies in which they use eye trackers (O: Observational, C: Controlled)

ID	Domain	Studies
P1	Energy	О
P2	Information Visualisation	С
Р3	Human-Computer Interaction	С
P4	Accounting	С
P5	Learning Analytics	О
P6	Neuroergonomics for Aerospace	C/O
P7	Human Factor and Human-Computer Interaction	C/O
P8	Machine Learning and Sensor Computing	О
P9	Information Visualisation	С
P10	Eyetracking Data Quality and AR UX	С
P11	AR/VR Innovations	О
P12	Simulation-based education	О
P13	Software Developer	О
P14	AR/VR Developer	О

"previsualise the data without any processing and explore the raw data" (P6) (FOR), "gain some intuition" (P4) (EVI) and "identify interesting events in the data faster" (P9) (SCH-SEN).

6.3.1. Current analysis tools

A bit less than half of the participants (6/14) reported using applications provided by the eye tracker manufacturers for their analysis. However, most participants also rely on *self-developed tools* (11/14). The reasons for this being that commercial software mostly handles only basic measures (2/14), and basic visualisations (3/14) and lacks important functionality for data exploration like filtering data outside AOIs (P2) (FOR), setting up accurate TWIs (P7) (FOR), and good support for dynamic content like video (P9) (EVI). Participants implement advanced metrics on their self-developed tools, like entropy (P7), and

novel visualisations such as time plot [66] (P7), edge bundling of saccades [67] (P6), and space time cube [68] (P9). P14 also mentioned developing tools to handle 360 degree images.

6.3.2. Data Exploration

The potential for eye tracking data exploration was identified by all the participants. They argued that the main feature that supports it is the interactive AOIs (FOR) (10/14). It is very easy to create them, and then compare the quantity of gaze movement within them (P3). P5 and P7 also appreciated that it is possible to visualise only the transition between them (FOR). P6, who is particularly interested in visual screening of instruments by pilots, suggested that it would be interesting to be able to filter saccades that go through AOIs in a specific order (FOR/SCH). In general the transitions between inside and outside of the AOIs were also considered as "helpful to know the glances coming in and out of the areas of interests" (P1) (EVI), more specifically the colour coding of the position of the fixation before going into the AOI and after (10/14). The histogram of such fixations around the AOI made it easy to understand (P4, P6, P10) (SEN). P10 stated that it was "clear for people who do not want to dive deep in the data" and P4 imagined it would be convenient to 'brush' AOIs across the entire workspace with this histogram to identify interesting areas early on (FOR).

Filtering and bundling are functionality aimed at reducing visible clutter, however, participants thought more could be done to reduce it (FOR). P2 proposed to filter saccades inside AOIs, and P6 suggested to cluster fixation more. The latter is justified by the uncertainty of the position of each fixation themselves (due to error in the measurement, mapping, etc.). While our system proposes various shapes for areas of interest, P9 suggested that being able to construct arbitrary polygonal shapes would to be more precise and better suited to their needs.

Another functionality considered interesting for data exploration is the timeline of fixations (10/14) (FOR/EVI). The linking of the timeline with the spatial visualisation (i.e. colour replicated in the timeline) gives a good indication of the distribution of the different types of saccades, it is "very useful as it helps to visualise changes in gaze patterns in a window" (P8) (EVI). More specifically, P2 suggested that being able to see the temporal distribution of before and after fixations (in the context of an AOI) provides good insights regarding users' strategies (SCH). P6 added that this was helped by the animated histogram which transitioned between the spatial view and the timeline (SCH). The definition of time windows around specific events can be important to understand specific aspects of the data: "Sometimes, you want to explore 10 seconds or 1 minute before and after an event" (P7) (EVI). The same participants found our tool allows for an accurate definition of such time windows compared to current manufacturer tools. As some of the events this participant focused on can repeat several times in one session, P7 would like to be able to define several of these windows in the timeline (TWIs).

Finally, 10/14 participants valued the ability to link the real video of the trial to explore their eye tracking datasets (EVI). Indeed, as P5 explained, lots of use cases imply a dynamic background, which is necessary to provide context information but hard to visualise with the data. In VETA, it is thus useful to have access to the raw video in order to "help answer questions about specific behaviour" (P7) (SCH) and to "link the data with the precise stimuli" (P8). P7, who analysed individual pilots behaviour, also envisioned using it to first provide quick analysis of the user behaviour (FOR), before visualising the data (EVI). Similarly, P8, who uses eye tracking to classify learning behaviour, considered the video as more important, and would use the data as a secondary source of information, a way of giving a "bigger picture" to the video (SEN). Finally, P10 suggested that it would be a good way of identifying when participants have to move their head to look from one area to another, which can be physically tiring (EVI).

6.3.3. Data Comparison

To compare data, and more generally gaze behaviour, is an important task in eye tracking data analysis [69]. Participants mentioned comparing between different conditions, or comparing directly between different participants (SEN). Edge bundling to aggregate saccades was considered by several participants as a good way of visually comparing different gaze behaviour, to highlight general patterns, and to detect outliers (6/14) (EVI), it also "helps to get rapid insights on the connections between different zones" (P6) (SEN). Participants also suggest that more formal comparison can be done with VETA using the small multiple functionality (9/14) (SCH-SEN). P2 stated that "Doing a side-byside comparison for multiple participants at a time saves more time to identify user patterns". While it is possible to load several users into our system, a majority of participants thought it would be useful to have an explicit participant management system (6/14). It would allow the ability to visualise specific conditions, or even trials (in the context of a controlled experiment). P7 suggested it would be interesting to be able to select one pattern in one user and show all the other users who have the same pattern. P9 went a bit further and proposed that the tool could classify the participants in function of their gaze behaviour. On a similar idea, P11 proposed to be able to compare participants' gaze to a "standard" trajectory, to, for instance, check if they follow the appropriate procedure responding to one event, or to compare to expert behaviour (EVI-SEN).

Most of the functionalities of VETA allow for visual comparisons, yet visualisation is not the only thing the participants need to perform their analysis. The majority of participants expect to be able to get quantitative metrics about participants' behaviour (7/14) (EVI). Eye tracking manufacturer software provide basic ones, but when needing more advanced metrics, participants had to develop their own tools. We asked which metrics participants would need, and we received a wide range of answers, including gaze distance inside AOIs (P2), number of transitions between AOIs (P4) and entropy (P7). Yet, they acknowless

edged it would be difficult to include all metrics in to one tool as people would always ask for more, and that other tools already provide these. To solve this problem, P7 suggested to implement a link from the visualisation tool to open source applications that provide eye tracking data metrics, such as Ogama¹¹.

30 6.3.4. Data Presentation

To present the results of the data analysis process to non-experts, visual representation of the insights are often used. Such visualisations are often hard to produce especially to illustrate complex gaze behaviours. For instance, P6 has to present findings regarding gaze behaviour of pilot trainees to their instructors, and to this end, provide them with "Annotated improved heatmaps", which highlight important components of the gaze behaviour (SCH). In our system, complexity of the visualisation can be decreased using edge bundling and filtering, while annotation can be used to explicitly emphasise interesting components of the visualisation (7/9 participants found it useful). P7 went further by explaining that VETA is simple enough to be used by non-experts allowing them to interact with the visualisations and thus grasp a better understanding of gaze data (FOR SEN). P9, however, warned that the amount of functionality provided could be overwhelming at first for non (eye tracking) experts.

7. Discussion

Throughout the design, development and evaluation of VETA, we have gained a wide understanding of the benefits of visual analytics for eye-tracking data.

Whilst we acknowledge there is further user-interface design and usability work to develop the digital prototype further, we have identified clear potential for using such a comprehensive visual analytics system for complex eye-tracking data, for a wide variety of domains. Here, we reflect on our findings and propose

¹¹http://www.ogama.net/

several design guidelines (shown in italies) for about visual eye-tracking analytics. Each of the guidelines cover all four of the stages (FOR, EVI, SCH, SEN) from the visual analytics sense-making loop (see Sec. 2).

7.1. Fluid and Dynamic Exploration

Analysts need to be able to link the spatial and temporal dimensions of the data:We found that the linking of spatial and temporal dimensions through the visualisations provided useful information about the transitions between time and space and allowed the dynamic ability to link between AOIs and TWIs succinetly. All experts found this feature useful and would explore the data both over time and space.

Analysts need to be able to interactively create and manipulate areas/time windows of interest:

An important part of the data exploration process is to actively seek information, by searching and filtering the data [7]. In the context of eye tracking, the most common method of filtering the data is to create AOIs (and TWIs), for example, these may be defined prior to study to test hypotheses. However, to support more exploratory analysis after the study is performed, it is important to allow the analyst to interactively create and manipulate them. In our prototype the dynamic AOIs allows for a highly interactive exploration of data. The expert evaluation indicated that these dynamic AOIs enhanced the experience of AOI analysis over using traditional eye tracking software. Some also felt that hand drawn AOIs would also be useful.

We found that the linking of spatial and temporal dimensions through the visualisations provided useful information about the transitions between time and space and allowed the dynamic ability to link between AOIs and TWIs succinctly. All experts found this feature useful and would explore the data both over time and space.

Analysts need to be able to filter and aggregate information quickly and interactively:

In order for analysts to understand patterns and structure in the gaze trajectories—but also to highlight outliers—it is important to be able to visually filter and aggregate them interactively [8] in general, with edge bundling [70] and with

gaze data [69]. We found the classification of saccades into 'glances' and 'short distance' were beneficial as a form of aggregation and provide additional context in our analysis. Bundling saccades on-the-fly provides the ability to see the bundling happening and thus helps the user understand how saccades are aggregated. In addition, combining type and directional bundling with their colour modes enables visual clarity to patterns (Fig. 3a).

Moreover the real simplicity of the directional histogram and time histogram, with animated transitions, were not only one of our favourite features of the interface, but a real hit with the experts. This demonstrates the power of simple visualisation of complex data. Many of the participants expressed that these simple, but dynamic views could be highly useful in exploring and understanding gaze behaviour in their own analysis.

Analysts need to be able to access the context of the session easily: In traditional eye tracking analysis software it can be hard to link the real-time video with the gaze trajectory data during the analysis. It is therefore difficult to infer the behaviour of participants at a specific time thus understanding their actions, and motivations in the context of the entire session. In VETA, in addition to the typical mapped background image to provide context, we proposed the ability to display the video of the eye tracking device (or screen capture) at anytime during analysis. This allows for the analyst to better understand what the participant is doing during a specific period of time and verify the accuracy of the exploration insights.

The quick transition from the data to the video was appreciated by the majority of the experts who saw a way of validating insights and more generally, to complete the bigger picture provided by the data with details regarding the behaviour of the participants. In our design, switching between video and data visualisation is designed to fill the screen and provide short snippets of video context to validate insights. We used a fade-in transition between the background image and the video, but, to avoid too much disagreement due to the context switching, it would also be possible to use image recognition to detect the position of the frame of the video that user wants to watch and then inter-

polate a transition between the background image and this frame [71]. Another solution would be to have a small insert screen showing the video that the user can maximise and minimise when needed.

7.2. The Need for Comparison

Analysts need to be able to compare gaze behaviours: Although the video and fixation information were found to be useful context, the interviews also identified the importance of customised metrics to understand the context numerically. In the motivational use case, we were interested in dynamically exploring the patterns of gaze behaviour and chose to add percentages of fixation time per AOI as this was interesting for our analysis of times spent at each location of their workspace. But many of our experts identified useful and different metrics to add to the interface. Providing further metrics which calculate dynamically could certainly be highly beneficial to the visual analytics process, yet further analysis of current systems and a wider group of eye tracking users would be needed to understand which measurements would be most useful in this context. One suggested option is to link VETA to open software such as Ogama, which would allow users to define their own measures. It could also be interesting to implement more complex measures and provide sequence analysis to extract viewing patterns [72]. Such measure has been shown to be beneficial in the context of air traffic control [73, 74].

Whilst in our use case comparing between participants was not anticipated, we did choose to implement small multiple views for comparing gaze patterns of one participant across multiple sessions and TWIs (e.g. Fig. 4). Through our evaluation we found that the small multiple comparisons were highly beneficial, and the ability to switch quickly between small multiple and specific context is also needed.

Most of the experts noted that they have to compare multiple participants in their analysis. This could involve embedding a small participant management system. This would allow users to aggregate and visualise participants, or conditions at the same time or in small multiples. In addition, it would also be possible to explore machine learning algorithms for the automatic classification of participants.

7.3. A Comprehensive and Collaborative Tool

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Analysts need to be able to save and share analytical state and record insights:

One important aspect of exploratory data analysis is the ability to save/load and share the state of the analysis during and after the analysis process. This allows collaborators to easily grasp the main steps of analysis that have been performed [10]. When dealing with a large quantity of data, analysts' working memory can quickly become overloaded [7]. Saving insights through making annotation records is useful to offload this working memory directly to the visualisation.

In our system, we provide a flexible solution for this context and it worked well for our needs. Further work, noted from our interviews could include attaching annotations to specific data points or time stamps.

The ability to enable the data to be tagged or coded with information would also be useful and could be utilised in the custom colour mode for distinguishing different tasks for example.

In addition to sharing the digital state of the system, the system has the ability to save a static image. For our motivational use case we needed to produce a report for non-expert users, so simple and good quality static imagery was needed. The ability for the system to be able to produce simple visualisations of complex eye-tracking data was verified through our interviews.

Finally, we acknowledge that there is a learning curve for the features of the system, and that some aspects are more intuitive than others, yet we found that the learning time is balanced by the time gained in the analysis of the data. In our use case (see Section 5) we found that the video link for verifying operator tasks meant this could be performed in a fraction of the time spent on similar activities in traditional software, and that many more insights could be identified through visual encoding and reducing visual clutter.

8. Conclusions

In this paper we introduce the VETA system, which provides a visual analytics workflow for exploratory analysis of in-the-wild eye tracking data. The VETA system comprehensively covers the key aspects of the visual analytics sense-making loop and is highly dynamic, to enable the visual exploration and presentation of complex eye-tracking data. We document insights from our applied use case and interviews with experienced eye-tracking analysts demonstrating the benefits and future potential for the system. Through our evaluation we identified a set of design guidelines for visual eye-tracking analysis and many further use cases and potential collaborations. We look forward to exploring the use of VETA in wider contexts.

Acknowledgements

The observational study that motivated the initial development of VETA was funded by the Australian Energy Market Operator (AEMO). We would like to thank all AEMO participants and all eye tracking experts who participated in the evaluation. We also acknowledge the use of Monash Business Behavioural Laboratory equipment in this project.

990 Author Contribution

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