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Eye Tracking Support for Visual Analytics Systems

Foundations, Current Applications, and Research Challenges

Submission 20

ABSTRACT

Visual analytics (VA) research provides helpful solutions for interactive visual data analysis when exploring large and complex datasets. Due to recent advances in eye tracking technology, promising opportunities arise to extend these traditional VA approaches. Therefore, we discuss foundations for eye tracking support in VA systems. We first review and discuss the structure and range of typical VA systems. Based on a widely used VA model, we present five comprehensive examples that cover a wide range of usage scenarios. Then, we demonstrate that the VA model can be used to systematically explore how concrete VA systems could be extended with eye tracking, to create supportive and adaptive analytics systems. This allows us to identify general research and application opportunities, and classify them into research themes. In a call for action, we map the road for future research to broaden the use of eye tracking and advance visual analytics.

CCS CONCEPTS

• **Human-centered computing** → **Visual analytics**; *Interactive systems and tools*; *Visualization theory, concepts and paradigms*;

KEYWORDS

Eye tracking, visual analytics, gaze-adaptive systems, support

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1 INTRODUCTION

Reliable eye tracking is now affordable enough that it can be integrated into regular workstations to support a variety of day-to-day work and leisure activities. This paper maps the road for using eye tracking in an area, in which this technology holds particular promise: Visual Analytics (VA).

VA describes a range of technologies that rely primarily on visual representations, interaction, and human-steered computation for analysts to explore, analyze, and make decisions with and from data. VA systems are, for example, an interactive website that allows people to visually explore and understand historical migration data from different perspectives; a biomedical desktop application that lets researchers analyze complex experimental data; or a crisis management command center setup involving many screens, real-time data, and multiple decision makers.

The common theme of VA systems is that they communicate with analysts primarily through the visual channel. We hypothesize that this makes VA systems particularly amenable to an integration with eye tracking. Up to now, only a few eye-based VA systems exist [Okoe et al. 2014; Shao et al. 2017; Silva et al. 2018, 2016b]. We believe that the next generation of VA systems could more broadly use eye tracking to infer and learn analysts' interests, goals, workflows, and tasks to proactively support them.

Our paper furthers this vision and lays the foundation for research on eye tracking supported VA systems. We first introduce a general VA model to the eye tracking community, describe and exemplify the range of possible VA contexts and solutions. Our first contribution is an approach that researchers and practitioners can use to explore how VA systems can be extended with eye tracking to create supportive and adaptive VA systems. Specifically, we show that the particularities of a concrete VA system can be described formally by a generic model whose facets can then be used to systematically consider ways in which eye tracking supports analysts' goals. Our second contribution is an inventory of research challenges that future research needs to tackle before the benefits of eye tracking supportive VA systems can materialize. We structure these challenges into research themes and map the road for researchers to broaden the use of eye tracking and advance VA.

2 RELATED WORK

Guidance systems [Collins et al. 2018] and recommender systems are emerging topics in VA and both demonstrated potential in supporting analysts. Using eye tracking we can potentially infer what people focus on [Just and Carpenter 1980]. Therefore, eye tracking offers a new and important channel through which applications and analysts can interact with each other. Because eye tracking is becoming affordable and allows systems to provide recommendations and guide analysts in data analysis processes, we discuss each of these topics individually, and give first hints about how to achieve eye tracking supported VA.

2.1 Recommender Systems and Eye Tracking

Recommender systems assist people in identifying potentially interesting items. With applications in many domains (e.g., e-commerce, information retrieval, or social media) recommendation technology is the target of constant improvements due to its real application value. These improvements and the use of pervasive techniques (e.g., eye tracking) in new recommendation applications were discussed in previous work [Felfernig et al. 2013]. Example recommender systems that integrate eye tracking were developed to help and guide people, select products [Castagnos et al. 2010; Castagnos and Pu 2010; Chen and Pu 2011], support reading, browse images, watch videos [Xu et al. 2008], assist air traffic controllers [Silva et al. 2015; Zhao et al. 2016], or recognize activities on cartographic maps [Kiefer et al. 2013]. In addition, advantages and pitfalls of using eye movement data in adaptive systems were discussed [Bednarik 2005]. Techniques to estimate human preferences were also developed, such as an evolutionary recommendation system [Jung et al. 2013], a support vector machine to distinguish user activities [Kiefer et al. 2013], and a collaborative filtering approach to increase the accuracy of recommendations [Song and Moon 2017]. [Also, Renner and Pfeiffer \[2017\] have used eye tracking for attention guiding in the context of assistance through augmented reality. In addition, Blattergerste et al. \[2018\] compared selection mechanisms in VR, which included eye gaze.](#)

2.2 Guidance in Visual Analytics

Guidance is an important component in the support of analysts when exploring large datasets. An example is the use of advising mechanisms that point analysts to interesting data features or clusters. Ceneda et al. [2017] presented a model to classify key aspects of guidance in VA. A selection of challenges associated with the implementation of guidance were then discussed by Collins et al. [2018], including the use of external inputs to guidance systems, such as eye tracking. Although this work already identifies eye tracking as a mean for guidance, it is not the main suggested mechanism, and its described role in the survey remained preliminary.

2.3 Visual Analytics and Eye Tracking

Eye tracking is also finding its way into evaluation of VA systems [Andrienko et al. 2012; Kurzhals et al. 2014]. In addition, a multitude of visualization techniques for analyzing eye movement data have been developed [Blascheck et al. 2017]. In addition, an analysis of VA systems using eye tracking and the visualization of

the collected eye movement data has been proposed in combination [Blascheck et al. 2016].

However, the above approaches did not discuss how eye tracking could guide analysts in their actual interactive analysis of data (i.e., while using a VA system). Only a few recent works proposed and implemented eye tracking support for VA systems. Steichen et al. [2013] investigated how to infer visualization tasks and cognitive abilities from eye movement data using bar and radar graphs. Silva et al. [2016a] used eye tracking to control a degree-of-interest display when exploring hierarchically organized data. Shao et al. [2017] proposed an exploration of scatter plot sets by recommending unseen scatter plots most dissimilar to seen ones. Silva et al. [2018] combined interaction with eye tracking and data features to compute rankings of time series and perform recommendations. These examples are encouraging and indicate the usefulness of integrating eye tracking into VA systems. However, they might not generalize well to certain tasks or data types.

[Up to now, a systematic review of challenges, and a road map of how to achieve eye tracking support for VA systems is missing. Therefore, we provide such a road map in this paper,](#) give examples of common VA systems for different domains and contexts, discuss how eye tracking can be integrated within these contexts, and organize research challenges associated with this endeavor.

3 BACKGROUND — VA PROCESS MODEL

VA encompasses technologies by which analysts relate to data by means of interactive data visualization, tightly integrated with data analysis algorithms, supporting the discovery of actionable insights into large and complex data. As a research field, VA builds on multiple disciplines, including analytical reasoning and human cognition, planning and decision making, visual representations and interaction techniques, data mining and machine learning, data management technologies, among others [Keim et al. 2010; Thomas and Cook 2005].

To describe a VA process, Keim et al. [2008] defined a well-known process-driven model (cf. Figure 1). As mentioned above, the VA process suggests that analysts aim to obtain insight into data by approaches that integrate data visualization and analysis. The visual analysis process is highly interactive, supporting analysts in interacting with the visualization (e.g., create views, drill down into views), and the data analysis model (e.g., select or configure analysis methods, clustering, classification, find suitable parameters).

To organize the discussion of how eye tracking can be integrated into VA systems, we consider the mentioned VA model. We enhance the four high-level building blocks of this VA model (Data, Visualization, Model, and Knowledge) with more detailed concepts (e.g., system, analysts' tasks, parameters, cf. Figure 1). Note, this specification serves our discussion goals. More encompassing extensions of the basic model have been suggested by others (e.g., Sacha et al. [2014], which details the knowledge generation process). [Next, we further explain the detailed concepts that we introduced into the VA model.](#)

Context. The context describes the application domain in which a VA process takes place. VA systems are used in many domains including scientific data analysis (e.g., social, environmental, physical and bio-medical research), engineering and production data

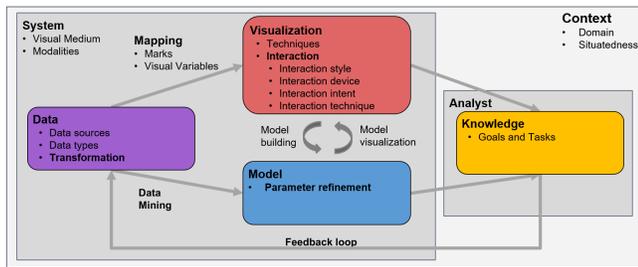


Figure 1: VA process model by Keim et al. [2008]. We further detail this model with context, system, and the analyst to discuss how to integrate eye tracking into VA systems.

analysis (e.g., input or output factors in production), or social media analysis (e.g., large networks and high-frequency messaging). An analyst may for example use a VA system in the lab, real-world emergency situations in the field using mobile devices, or in the office. The context relates to both the system aspects as well as the analysis goals and tasks.

Analyst. The range of analysts using VA systems is broad. We can divide them into experts and novices in a specific domain or in visualization. A domain and visualization expert could be a data journalist, whereas a domain expert with less knowledge in visualization could be a biologist. Typically, visualization researchers are experts in the field of visualization, however, they do not necessarily have specific domain knowledge. Lastly, an increasing number of people that are neither domain nor visualization experts (general public) are interested in analyzing data.

Knowledge. Analysts using a VA system usually have multiple specific goals in mind. These goals can be reached by performing multiple analytic tasks. Shneiderman [1996] defined a widely-used taxonomy of analytic tasks that are universally applicable: overview, zoom, filter, details-on-demand, relate, history, and extract tasks. Similarly, Pike et al. [2009] defined goals and tasks of analysts. However, they further divided the analytic discourse of an analyst with a VA system into low-level choices versus high-level goals for an investigated problem. Knowledge obtained from the VA can occur in implicit or explicit form [Federico et al. 2017].

System. The VA system comprises the implementation of a VA design that runs on a specific hardware and software platform. It typically involves different visual media and interaction modalities. The range spans from desktop computers to tablets, smartphones, smart watches, public or wall-sized displays, virtual and immersive environments. The system specifications determine the many performance aspects it may deliver (e.g., response time, display resolutions, interaction modalities). Recently, natural user interfaces like voice and gesture recognition are being considered, in addition to typical desktop interaction modalities. Eye tracking capabilities can also extend these systems.

Data. The data analyzed in a VA system originates from different data sources and represent multiple data types. The data sources can be from real world measurements and observations (e.g., medical images, seismic data, astronomy) or theoretical/virtual world measurements using mathematical and simulation models (e.g., molecular dynamics, meteorology, economic or financial modeling, simulation). The data from these sources can have different

data types. Shneiderman [1996] defines seven data types: 1D, 2D, 3D, temporal, multi-dimensional, hierarchical (tree), and network. Typically, the first step before analyzing the data is to pre-process and transform the data into an appropriate form for further exploration. This may include data cleansing, normalization, grouping, or integration of multiple heterogeneous data sources [Keim et al. 2008]. Important aspects of data influencing the analysis process include the quality of the data that may be affected by missing data values, erroneous measurements, uncertainty, and others.

Visualization. After the data is transformed into an appropriate form, it can be mapped to a visualization technique. The building blocks of a visualization according to Bertin [1967] are marks (points, line, areas) and visual variables (size, form, value, orientation, position, color, and texture). The different types of visualizations based on groups of imposition are also classified (diagrams, networks, maps, symbols) and types of imposition, divided into arrangement and construction (rectilinear, circular, orthogonal, or polar). Some examples based on this classification are (stacked) bar charts, pie charts, sunburst charts, node-link diagrams, scatter plots, or map representations.

Interaction. To reach their goals, analysts perform multiple tasks and interact with VA systems. Preim and Dachsel [2010] considers interaction style (e.g., direct manipulation, speech, gestures, menus) and interaction techniques, (e.g., selection, brushing, dynamic queries). Interaction further depends on devices (e.g., keyboard, pointing, touch) and on intent [Haag et al. 2013]. Many taxonomies exist for interaction intent [Amar and Stasko 2004; Brehmer and Munzner 2013; Munzner 2014; von Landesberger et al. 2014]. The most well-known and established by Yi et al. [2007] defined select (mark as interesting), explore (show something else), reconfigure (show different arrangement), encode (show different representation), abstract/elaborate (show more/less detail), filter (show conditionally), and connect (show related items). Eye tracking information can complement classic interaction operations. In our work, we focus on the inference of analysts' goals, states, etc. and on how to support the analysis process thereby.

Model. The model specifies the data analysis method to be applied to the data, and to support the analysis goals. Here, many different methods from statistics and machine learning can be considered. Examples can include regression modeling, outlier and anomaly detection, similarity search, cluster analysis or classification, and frequent pattern mining [Han et al. 2011].

The analysis goal and data at hand influence the choice of the model. VA systems often aim to integrate data modeling with visualization via interaction [Endert et al. 2017]. For example, model tools can be applied to visualize the mining process, or serve as an interface for analysts to select and compare model parameters.

4 INTEGRATION OF EYE TRACKING INTO EXAMPLE VISUAL ANALYTICS SYSTEMS

To demonstrate how we can integrate eye tracking into VA systems, we present several examples from different domains: business intelligence, law enforcement, immersive analytics, situated analytics, and geographic information systems. We chose these systems to cover a wide range of domains and different types of usages (i.e.,

desktop, mobile, virtual, augmented, and mixed reality). **These example VA systems do not include an integration of eye tracking. However, we discuss for each how eye tracking could be integrated and how to infer analysts interests.** We use the VA model described in Section 3 to identify promising extensions to these example VA systems by integrating novel eye tracking technologies. We also identify challenges of such an integration. **The extensions and challenges presented are usually common to all of the VA systems discussed and could even be generalized to other applications.** Unless stated otherwise, we assume that desktop applications are used in an office setup with reliable eye tracking.

4.1 Tableau – Business Intelligence Analytics

Tableau [2019] (cf. Figure 2 A) is a business intelligence and analytics software intended for analysts from all types of sciences and different domains (e.g., energy, education, government, finances, manufacturing, health care, insurance, sports, law). It offers desktop as well as tablet, web, and embedded versions. It provides functionality for analysts to get an overview of data, filter it, and inspect details. An exhaustive history is created, which is available even after Tableau is closed. To a lesser extent, Tableau includes the option to relate and extract data. Zooming is only available for certain visualization techniques.

Analysts can load data from a file or connect to a server. Tableau supports many common data and charting types. An analyst can filter, perform calculations, and integrate data from multiple sources. The visualization techniques that Tableau provides ranges from simple data tables to diagrams such as bar, pie, line, area charts, box plots, Gantt and bubble charts, maps, heat maps, tree maps, and scatter plots. To interact with Tableau, analysts can directly manipulate data points, use menus and dialogues. In Tableau desktop, one can use a classical keyboard and mouse pointing interaction. On a tablet gestures are used, as analysts interact via touch screen. The interaction techniques supported in Tableau include the selection of one or multiple data points and brushing to highlight the same data points in multiple views. Based on the taxonomy by Yi et al. [2007], Tableau supports different intents of an analyst (i.e., select, explore, reconfigure, encode, abstract/elaborate, and filter). Tableau offers functionality for automatic data analysis such as outlier detection, clustering, and regression analysis.

Benefits and challenges of an eye tracking integration. The analysts' expertise level when using Tableau varies, as in several other VA applications. Hence, detecting analyst expertise using eye tracking, and adapting the UI or application behavior can provide appropriate guidance. A novice might feel lost while using Tableau, therefore, detecting when a person is "lost" (e.g., based on number of rapid saccades between AOIs) could trigger a help function dependant on which features analysts are working on. When an expert is detected, the help function could be triggered at a later stage than it would normally for a novice.

Tableau offers many visualization types that could be created by choosing different dimensions and measures as well as by specifying marks in a panel [Bertin 1967]. Integrating eye tracking into visualization creation could be supported, e.g., by suggesting which dimension, measure, mark, or visualization could be chosen based

on analysts' focus. This would help an analyst explore the data exhaustively. Suggestions could also be given based on collaborative efforts. If multiple analysts are exploring the same dataset, the software could display suggestions based on previously collected eye movement data.

Exploring data in Tableau could be enhanced by automatically highlighting data elements when an analyst focuses on them for an amount of time. In addition, a combination of keyboard interactions and fixation duration could perform gaze-based filtering. Instead of dragging a dimension or measure with the mouse to the filter panel, an analyst could instead look at one of them, the system highlights it, and triggered by a keyboard shortcut it automatically opens the filter menu to select which elements should be excluded or included.

Supporting analysts during the data mining process in Tableau is similar to creating new visualizations. A separate pane next to the data pane offers functionality for automatic analysis (e.g., clustering). Based on where an analyst is looking at, suggestions and guidance could be given to help with the data mining.

4.2 Mobile VA for Law Enforcement

Razip et al. [2014] worked with a consortium of law enforcement agencies to develop and evaluate a VA system (cf. Figure 2 B) to aid patrol officers, detectives, and crime analysts. It was intended to be used on desktops inside offices, and in the field, on mobile devices.

The system stores, collates, and displays geographically and temporally annotated crime reports. It consists of a map onto which crime incidents are plotted as color-coded points; an interactive time series view that plots incident counts over time; a calendar view showing incident counts for specific dates; and an interactive clock view to plot incident counts for concrete times of day. It also retrieves and overlays census information onto the map. All views are linked through brushing interactions in which a selection in one view is mirrored into others.

A study with officers indicated that the system is used differently across the multiple categories of analysts. Shift supervisors pointed out that they used the temporal reporting features in conjunction with the geo-spatial features to assist in resource allocation planning. Patrol officers primarily used a mobile version in the field – geo-spatial and temporal filtering allowed an increased awareness of their area of patrol responsibility. Mobile analysts referred the need for voice controlled commands to perform common functions, as their hands were often busy with other tasks. Detectives used the system to solve crimes, for example, by investigating crime patterns. Crime analysts used it to generate insights into patterns and analyze trends in crime that they reported to their police departments.

Benefits and challenges of an eye tracking integration. Analysts using desktop computers are stationary in front of large screens and their eyes can be tracked accurately. In mobile contexts, analysts' positioning in relation to the screen, lighting conditions, and screen sizes are variable, making accurate eye tracking more difficult. Task-support in each mode should account for different degrees of uncertainty in the eye movement data they rely on.

Different eye tracking support could be offered depending on the system's types of users. To detectives and crime analysts who

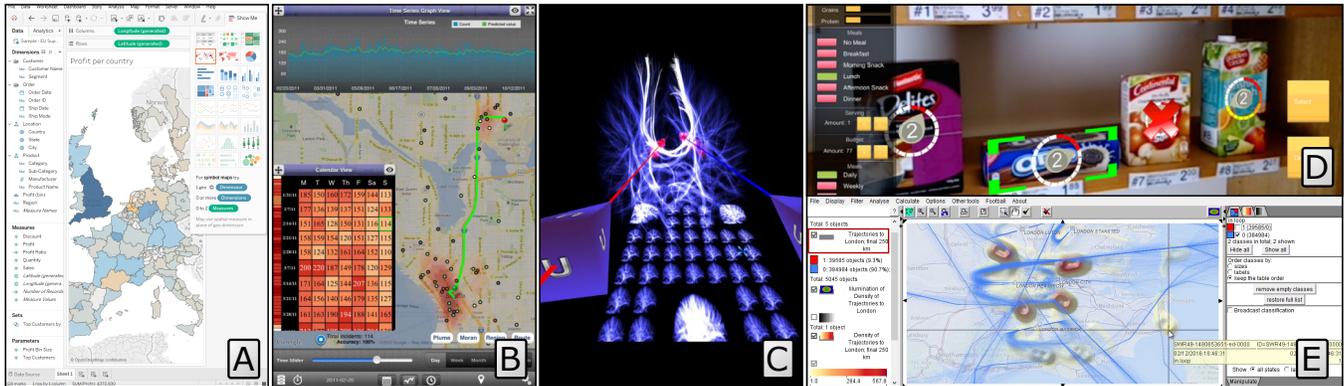


Figure 2: VA Systems: A) Tableau, B) Law enforcement analytics, C) FiberClay, D) Situated Analytics, E) V-Analytics.

seek patterns in the data, the system could offer analytic support in the form of recommendations. Examples are analysis recommendations, e.g., “You looked at correlations between X and Y, you may be interested in Z as it is correlated with X”, or collaborative recommendations, e.g., “This data may be of interest as it caught the attention of many other analysts”. Patrol officers use the mobile version of the system and explicitly requested a reduced reliance on manual interactions. Eye tracking could complement voice interaction by helping to disambiguate references made in natural language commands. For example, based on an analyst’s current gaze activity, the question “When are such crimes happening in this area?” could be specified as “When are burglaries happening around the intersection of street X and Y?”. Overall, eye tracking could be used to identify and support low-level visual tasks. The system could infer that analysts are searching for blue dots and visually emphasize them. It could also detect that analysts are trying to connect visual information across multiple views and highlight it in all views.

As shown in Figure 2 C), the system integrates multiple views each with relatively distinct functions. One may automatically detect which views analysts are looking, and aim to detect from this analysts tasks, interests, and favorite ways of visualizing data. Within each view, we could detect specific visual elements that analysts fixate on, the accuracy would depend on the element’s size, shape, and proximity to other elements. The system displays much of the information as point-like glyphs and these should be easier to track compared to more complex shapes such as lines [Okoe et al. 2014]. It is also important to note that the system is not interaction-heavy, analysts could extract insights by just looking at the linked visualizations without interacting with them. In a system such as this, eye tracking could tell us a lot about analysts’ interests and intentions whereas tracking manual interactions alone would not. This differs from some interactive systems that rely heavily on details on demand and navigation and in which manual interactions are a sufficiently reliable proxy for analyst interest.

4.3 FiberClay – Visual Analytics in VR

FiberClay (cf. Figure 2 C) works with head-mounted displays and hand-held controllers [Hurter et al. 2019]. It was designed for the visualization of trajectories. Users navigate the virtual 3D space

by orienting the camera with their head posture and then use controllers to move and scale the view. Alternatively, they have a 2D plane for adjusting continuous view and layout parameters. The plane is filled with tiles that show thumbnails to guide analysts in possible adjustments, including the switch to 2D projections of the trajectories, allowing them to follow an airplane’s history of flight levels.

Once analysts have chosen their view on the data, they can select large data ranges or specific trajectories using virtual rays that represent physical hand-held controllers. They press buttons and select or deselect all intersecting trajectories, essentially sculpting a query in 2D or 3D. The system gives an intuitive representation of spatial data as it matches the display dimensions. Trajectories of air planes and neural cell connections can be shown and analyzed. Simultaneously, time series of single parameters can be visualized in 2D, matching regular and well-known techniques from outside the virtual environment. The system runs smoothly on current hardware and it is well adapted for intuitive interaction through head and hand movement. It can be operated while sitting on a chair and does not require free body movement.

Benefits and challenges of an eye tracking integration. Integration of eye tracking in the FiberClay system could lead to several changes in multiple areas. Hurter et al. [2019] minimize body movement and potential collisions by providing interaction through hand-held controllers and head movements, allowing an analyst to be stationary. Using gaze as an interaction technique, arm movements could be reduced to pressing buttons. Visually focusing on virtual objects that are near or far could be suitable for depth selection within VR headsets. However, the actual focal distance of drawn objects is physically limited to a static value and could lead to confusion. The depth selection issue for two crossing gaze rays, could be ameliorated if the system automatically moves the camera to a position that is orthogonal to data points currently being looked at. Frequent automatic view changes could confuse analysts, destroy their mental map, and make the entire system unusable. However, it could be combined with explicit interaction through buttons. *Virtual environments often have high performance demands. Using eye movement data, developers can implement dynamic foveated rendering and therefore increase frame rates in order to ameliorate issues with simulator sickness*

[Marianos 2018]. Eyes have a narrow field of view at full resolution, and blurring occurs outside the fovea region on the retina. Rendering specific parts of objects or scenes that analysts are able to fully grasp (by using interpupillary distance and the position of the eye relative to the lenses) might have several advantages. The same technique can be used to automatically adapt dynamically generated content (i.e., procedural generation of virtual scenes according to the deployment of attention and physical differences of analysts) to improve the overall user experience (e.g., story-line in a game). At the same time, gaze reflects personal interest and could give the system an indication of what data items are most interesting to analysts [Just and Carpenter 1980]. The 2D parameter navigation described in Section 4.3 could highlight the interesting data points and help analysts manually find more suitable representations. Alternatively, the system could automatically select glyphs with less overdraw in the region of interest, or suggest completely different views and visualizations that make the target data more readable. Notifications are a possible way of making such suggestions and are often placed on a specific location in regular desktop environments. In an immersive environment, however, there might not be a single suitable static placing option. Notifications might require explicit input to become visible and could be coupled with sound alerts.

People with refraction errors need to wear glasses that might not fit inside head-mounted displays. Additional optics could correct such defects and might be automatically adjusted to the person when combined with eye tracking. To achieve this, the underlying software could show test patterns with increasingly finer shapes and check real-time gaze data for their visibility.

4.4 Situated Analytics – Analytical Tools in AR

ElSayed et al. [2016] presented Situated Analytics (SA), real-time interaction techniques (cf. Figure 2 D). Based on two domains, it provides analytic reasoning in the physical space: VA and Augmented Reality (AR).

The authors consider the question of how SA can be beneficial for data exploration and information comprehension. It is stated that SA can enhance decision making in three ways. First, clear information presentation by directly associating information with relevant physical objects. Second, more natural interaction for information exploration by touching and manipulating physical objects. Third, more sophisticated information analysis providing both contextual and overall information.

SA is a novel combination of real-time interaction and visualization techniques to allow the exploration and analysis of information about objects in a specific physical environment. Analysts can visually interact with information and objects in AR and access attached information. They can also view and compare information associated with multiple physical objects.

Benefits and challenges of an eye tracking integration. Augmentation by eye tracking support in the case of the SA system could consider multiple aspects. In highly sensitive jobs, eye tracking based systems might be used for continuous security and identification checks. Multiple analysts could share the same AR device and adjustment to the profile to analysts' preferences could be done automatically.

While using this VA system, analysts focus their attention on both virtual and physical objects. Eye tracking enables interaction with objects using fewer steps (e.g., users look at objects and give commands using voice, and a mapping between gaze and object detection provides contextual information). In collaboration scenarios, information on gaze direction, emotion and interests may be used to support social interaction between analysts. For example, one analyst may be given hints about other analysts' gazes, which may enable an interest-based connection between them. It also may open new possibilities for remote support and learning scenarios (e.g., changes in one analyst's focus could be synchronized to the camera views on other remote systems).

Head-pointing could be replaced by eye-pointing. It might be a more accurate representation of how humans interact with the real world (i.e., hand-eye coordination could be implemented by correlating gaze-aim with action-finger-pointing). Visible traces for areas focused on by analysts could be added (e.g., each analyst leaves a color or pattern trace to be followed by others when exploring a dataset). If analysts focus on a wrong direction or follow an inefficient analysis sequence, navigational hints are activated (e.g., arrows, contours, blurs, color shifts, voice/binaural sounds, or messages).

Knowing if analysts are focusing on an object or not, allows to update information only when desired to minimize distractions and resources usage. This technique could infer if objects in the scene are attended and respective importance, allowing the guidance of analysts to unattended or hidden objects. Information changes could be enabled in a dynamic way to achieve adaptation of the overall story in a more engaging way. Using information about previous interests together with analysts' interactions, a new simulation and inference model could be created (e.g., using reinforcement learning) to learn how analysts behave in different situations. The VA system could then decide when and which information to display.

4.5 V-Analytics – Visual Analytics for GIS

Geographic Information Systems (GIS) are used for storing, representing, analyzing, and visualizing spatio-temporal data [O'Sullivan and Unwin 2014]. V-Analytics (known as CommonGIS, cf. Figure 2 E) is a VA platform offering a multitude of analysis methods and visualization possibilities for spatio-temporal data, most prominently spatio-temporal trajectories for movement data analysis [Andrienko et al. 2013]. The software has supported research in various domains, such as mobility and transport, aviation and air traffic analysis [Andrienko et al. 2018], sports [Andrienko et al. 2017], or animal movement. Although V-Analytics is mainly a platform for researchers, it is freely available [Andrienko and Andrienko 2019] and can be used by anyone for different types of spatio-temporal data sources. The software offers various methods for visual analysis of trajectories (single or groups). It allows comparative analyses that focus on discovering and understanding patterns resulting from differences in spatio-temporal distributions and contexts [Andrienko et al. 2019]. V-Analytics contains tools for data transformation, generalization and aggregation, clustering methods, and interaction techniques. Visualization techniques include 2D and 3D maps, space-time cubes, flow maps, histograms, and density distribution.

Benefits and challenges of an eye tracking integration. Integrating eye tracking support into V-Analytics could encompass diverse items. V-Analytics allows the visualization of maps, trajectories, diagrams, graphs. Using eye movements the system could detect that an analyst missed an important item and provide automatic highlighting. [Visual attention is an important aspect in eye tracking](#). [Boris et al. \[2017\] presented a generalized process for visual attention analysis with eye movement data and Frutos-Pascual et al. \[2015\] assessed visual attention using eye gaze data as a way to identify children’s behavior in attention-enhancement therapies.](#) Analysts’ visual attention could be used to include interaction improvements by automatically adapting the placement of legends and content in maps according to analysts’ gaze [Göbel et al. 2018]. Using a remote eye tracker within the desktop environment would ensure sufficiently high accuracy of the eye movement data to detect the region where analysts are looking at and relate analysts’ attention with the task. When solving a problem together as a team, such collaborative work could be facilitated if one analyst could always know where the other analysts are currently looking at (e.g., to which part of the trajectory the other analyst is interested in or already handling).

Eye tracking would enable support during various analytic tasks, for example, the system could actively recommend important data correlations and visual items. The system could create a graph of attended items and keep an historic track that analysts could use for posterior analysis (i.e., data provenance), reconstruction of exploration strategy, or to be simply utilized by other less experienced analysts. A model could be created to decide when to automatically support analysts or not, based on their gaze behaviour. The model would need to be able to decide the right balance between analysts’ control and automatic support as well as adaptation.

5 OPPORTUNITIES AND CHALLENGES

We identified research opportunities associated with the creation of gaze enabled VA systems. We did so by aggregating, extrapolating, and organizing opportunities and challenges discussed in Section 4, by drawing from our own research experiences, and from existing literature [Alam and Jianu 2017; Okoe et al. 2014; Shao et al. 2017; Silva et al. 2018, 2015, 2016a,b]. We then clustered the opportunities and challenges into five critical research themes that we think align with interests and expertise in the eye tracking and visualization communities. The themes also correspond to different stages or envisioned prerequisites in the development of eye tracking supported VA systems: (i) reliable and accurate collection of raw eye movement data; (ii) translation of raw eye movements into data and visualization semantics; (iii) modelling of higher-level intents; (iv) provision of adaptive support; (v) and ensuring privacy. Our work suggests research opportunities and motivates the eye tracking and visualization communities to materialize eye tracking supportive VA systems.

5.1 Theme 1: Reliable Eye Tracking

At their core, eye tracking supportive VA systems rely on the improvement of unobstructed, affordable, and reliable eye tracking technologies, across different VA system platforms, including desktop computers, mobile devices such as tablets, phones, watches,

public or wall-sized displays, and embedded into virtual and immersive environments (cf. Section 4).

Eye tracking in desktop settings has become affordable and relatively accurate. This is due to large screens, stable lighting, and analysts limited movement. Conversely, emerging VA usage contexts such as the ones exemplified in Section 4 are significantly more problematic. A range of problems needs to be solved before eye tracking can be used in practical VA settings. Among these, and arranged by usage context, are:

- Varying light conditions and viewing angles (e.g., mobile usage like in *Mobile VA for Law Enforcement*, see Section 4.2)
- Energy efficiency and remote communication capabilities to increase eye tracking autonomy (e.g., mobile usage like in the *Mobile VA for Law Enforcement*, or virtual environments like in *FiberClay*, see Section 4.3, and *Situated Analytics AR*, see Section 4.4)
- Accuracy for collaboration (e.g., wall-sized displays or dashboards like in *Tableau*, see Section 4.1, or *V-Analytics*, see Section 4.5, and in virtual environments like in *FiberClay*, see Section 4.3 and *Situated Analytics*, see Section 4.4)
- Head-mounted accuracy and multiple infrared interference (e.g., CAVE VR systems or exterior applications like in *FiberClay*, see Section 4.3, and *Situated Analytics*, see Section 4.4)
- Automatic, unobtrusive calibration and re-calibration (all VA systems examples)
- Standardized SDKs for gaze metrics and reporting (all VA systems examples)

5.2 Theme 2: Mapping Eye Movement Data to Visualizations

Mapping fixations onto rectangular, non-overlapping, and relatively large AOIs has received considerable attention in the eye tracking community. However, VA systems build on visualizations that compose complex drawing primitives. Such primitives include not just shapes that are approximated by rectangular/circular outlines but also overlap as interleaved curves and shapes of different sizes.

Thus, considering that a visual primitive is viewed only if a fixation lands within its bounds, may not suffice. It is likely that for VA systems, each fixation translates into a set of probabilities that one or more visual primitives have been viewed. Such probabilities depend on the complexity and density of primitives in the visualization and resolution of the eye tracker [Jianu and Alam 2018]. Moreover, people do not view visualizations in a random order, they follow patterns determined by the structure of the visualization, analysts’ visual tasks, and their manual interactions. This information can help determine viewed elements with an increased accuracy [Alam and Jianu 2017]. A thorough understanding of how gaze information translates into viewing likelihoods, how to increase the accuracy of detection, and how to work around the uncertainties associated with it, is currently lacking. Also, in virtual environments, new heuristics to determine the actual gazed object (i.e., gaze-to-object mapping) need to be developed.

Moreover, the visual elements that VA systems build on, they depict data. Systems can infer data elements and data features that analysts are interested in by detecting when visual representations are focused (e.g., Section 4.1). How to do this for different types

of visualizations and data is still partially unknown. Libraries and SDKs that can integrate such knowledge and allow visualization designers to easily translate eye movement data into probabilities that their elements have been viewed, as well as maintaining histories of this during run-time would further the proposed vision.

5.3 Theme 3: Modelling of Higher-level Intents

Accurate raw eye movement data and attention maps on visualization elements needs to be converted into models of expertise (e.g., Section 4.2), understanding, goals, and tasks. New systems should be aware of past, current, and future intentions. This should be possible if a model maps the intentions and needs of analysts in a continuous way, by creating an online support model based on multiple features (e.g., eye movement data, interaction, feedback, sensors, mental model, reverse engineering during the exploration of large datasets, etc.). The investigation of how and when to best guide, recommend, or adapt is an important research topic. A reliable inference of the action-intent would enable the support of analysts, for example, help select data faster, interactively load more data into a view, reduce interaction by providing auto-navigation, or provide step-by-step instructions to accomplish a task.

Machine learning techniques may help. These range from training offline models with eye movement data to improve collaborative recommendations, to continuous tracking systems that use real-time eye movement data to feed an online model. The model can adjust its weights according to the variations in the analysts' visual interests. These models can combine multiple features that are directly or indirectly linked to the gaze of a person (i.e., combination of gaze duration on AOIs, a history of interesting data features through time, multiple sensors, plus several actions or decisions that analysts make using a keyboard, control pad, or voice). In Sections 2 and 4 we refer and discuss multiple examples of potential solutions. This combination of features increases the capability of detecting the context (e.g., Section 4.4). It might be vital for the next stage during which we want to support the analysts.

5.4 Theme 4: Adaptive Support

Research on the themes described above would create the premise for generating a variety of support mechanisms. *Interaction Support* could help analysts perform low level interactions (e.g., navigating to some data of interest) and data-reading tasks (e.g., determining if two nodes are connected in a node-link diagram [Okoe et al. 2014]). *Recommendations* about unexplored but potentially useful data could be made to analysts based on historical or online models of their interests. *Guidance* (e.g., Section 4.1) would consist of higher level support in which systems help users through novel methodologies and techniques that fit the problems to be solved. *Dynamic Adaptation* would allow systems to detect and match analysts' cognitive and analytic particularities (e.g., Section 4.3), their workflows, preferences, interests and needs.

It is not obvious how to best communicate such support to analysts in a way that is helpful yet not disruptive. *In-situ highlighting and overlays* (e.g., Section 4.5) could be used to show support directly in visualizations (e.g., marking suggested items). *Recommendation panels* could show support in separate panels, perhaps along with more detailed suggestions that analysts could consult on

demand. Perhaps *other modalities* such as speech or haptics could add dimensions to communication between analysts and systems.

5.5 Theme 5: Ensuring Privacy

Ensuring analysts' privacy is paramount in allowing eye tracking based VA systems to be adopted. Investment from big players like Google, Facebook, Microsoft or Twitter will increase the awareness for protection of analysts. A careful debate around the potentials and misuses of the technology and specific guidelines for user identification (e.g., Section 4.4) and privacy protection are needed.

Eye tracking adds elusive capabilities to marketing profiling. Sensitive information can be captured by measuring gaze duration or pupil dilation [Blog 2017] and, while clicking can be avoided, willfully not looking at content is difficult. Eye tracking technology is already available in MR as well as VR systems and could soon be widely used in TVs, smartphones, or cars. Commercials can be embedded into free VR games for profiling [Law 2017]. Eye tracking can be integrated into surveillance systems to anticipate next actions and thus invade peoples' privacy [Liebling and Preibusch 2014; Stanley 2013]. **Additionally, eye tracking can reveal disorders with high accuracy (up to 87%)** [Lagun et al. 2011; Terao et al. 2017; Ting et al. 2014], for example, cognitive disorders (e.g., autism, attention deficit disorder, dyslexia); psychological disorders (e.g., Schizophrenia, Parkinson, Alzheimer's, post-traumas, eating disorders); HIV (AIDS Dementia Complex); and behavioral disorders (e.g., lies, drug and alcohol use, fatigue and distraction).

Eye-tracking provides a potentially dangerous channel into peoples' identity and into how they think, analyze, process, or interact with information. The long awaited arrival of affordable eye tracking systems could also bring a new generation of privacy invasion. Remedies and avenues to ensure the privacy of analysts using eye tracking supportive VA systems need to be researched. New eye tracking APIs could provide notice about the data being collected and analysts could be able to control which data is shared. Policy changes to provide minimum privacy guarantees can be made. Liebling et al. [2014] point to both privacy challenges and eye tracking potentials for research, engineering, policy makers and businesses.

6 CONCLUSION

In this paper we discussed the vision and lay the foundation for research on eye tracking supported VA systems. We first introduced a general VA model, then we described and exemplified the range of possible VA systems. Based on these example VA systems, we identified promising extensions through integration of eye tracking technology, and discussed potential research challenges that future research needs to tackle before the benefits of eye tracking supportive VA systems can materialize. Finally, we aggregated, extrapolated, and organized these challenges of such an eye tracking integration, extracted five research themes, and mapped the road for researchers to broaden the use of eye tracking and advance visual analytics.

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