Challenges and Perspectives in Big Eye-Movement Data Visual Analytics

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***Abstract*—Eye tracking has become an important technology to understand where and when people pay visual attention to a scene. Nowadays, eye tracking technology is moving from the laboratory to the real-world, producing more data at higher rates with extensive amounts of different data types. If this trend continues, eye tracking moves into the direction of big data. This requires developing new evaluation approaches beyond statistical analysis and visual inspection to find patterns in the data. As in big data analysis, visual analytics is one possible direction for eye movement data analysis. We look at current visual analytics methods and discuss how they can be applied to big eye-movement data. In this position paper we describe challenges for big eye-movement data visual analytics and discuss which techniques may be useful to address these challenges. Finally, we describe a number of potential scenarios for big eye-movement data.**

I. Introduction

The exploration of visual attention viewers pay or paid to a scene remains a challenging issue. Especially, when the goal is to derive common reading strategies from a large number of people, analysis techniques are missing. Statistical methods are often too restricted to find patterns in the data, and traditional visualizations such as attention map or scanpath visualizations reach their limit if the number of people being eye tracked grows. This analysis problem is also due to progress in hardware technology taking place in the field of eye tracking. The technology for eye tracking devices is steadily improving. These devices are becoming affordable and applicable to widespread scenarios. Eye tracking research is moving from laboratory experiments to field and real-world studies and applications. This shift to the real world is also due to eye tracking becoming available to non-experts. If eye tracking is accessible by a vast amount of people, massive eye movement data will be generated that has to be analyzed. This increase in volume, velocity, and variety leads to big eye-movement data.

With the growing amount of data, we question if traditional approaches like statistical analysis and visual inspection can keep up with this trend. In the past, eye tracking experiments were conducted in a laboratory with some ten up to a few hundred participants. A typical evaluation of eye tracking experiments took a couple of weeks. The goals of these studies were to evaluate how users perceive objects, investigate the usability of systems, or find out how users can interact with a visualization. However, if eye tracking becomes available to the broad public, new research questions develop. For example, tracking thousands of people allows one to refine perceptual models, investigate different types of groups, or find patterns in consumer behavior. This leads to an increase in people being eye tracked, the data becomes more complex with additional attributes, and classical evaluation methods reach their limits.

In this position paper, we describe challenges of big eye-movement data visual analytics. Moreover, we discuss possible perspectives how analysis techniques can be adapted for novel big data scenarios in the field of eye tracking. Visual analytics is a good means to derive knowledge from spatio-temporal data sets because analytic reasoning, human-computer interaction, and visualization are combined as key components. We illustrate our ideas investigating if today's analysis, visualization, and interaction techniques are useful and effective to handle big eye-movement data.

II. Related Work

There are numerous definitions of the term *big data*. Ward and Barker [1] define big data as "a term describing the storage and analysis of large and or complex data sets using a series of techniques including, but not limited to: NoSQL, MapReduce and machine learning". De Mauro et al. [2] state that "Big Data represents the information assets characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value" and Hashem et al. [3] describe big data as "a set of techniques and technologies that require new forms of integration to uncover large hidden values from large datasets that are diverse, complex, and of a massive scale". All three definitions include the three V's of big data Laney [4] defined: *Volume*, *Velocity*, and *Variety*. The analytical methods to evaluate big data include but are not limited to cluster analysis, machine learning, and visualization [2]. Combining this with perceptual abilities of a human analyst leads to an evaluation of big data using visual analytics approaches [5], [6], [7]. The combination of these individual steps can be helpful to reveal visual patterns, trends, or correlations, but also anomalies and outliers.

In recent years, eye tracking research has become an established method to evaluate eye movement behavior of participants. Eye tracking is applied in different research fields such as marketing, psychology, neuroscience, human-computer interaction, or visualization [8]. Typically, eye movements are collected with remote eye tracking systems, eye tracking glasses, and recently also interactive eye tracking devices or smart phones [9]. This leads to an increase in the amount and complexity of data collected, the three V's of big data. Nowadays, the volume of eye movement data collected is increasing. New technologies, such as head-mounted eye tracking glasses or higher tracking speeds, are developed. More participants are tracked (up to 500) and the complexity of stimuli becomes larger. Eye tracking studies also take longer, e.g., a car driving scenario lasting for 30 minutes [10] or longer. The speed of data generation (velocity) is increasing

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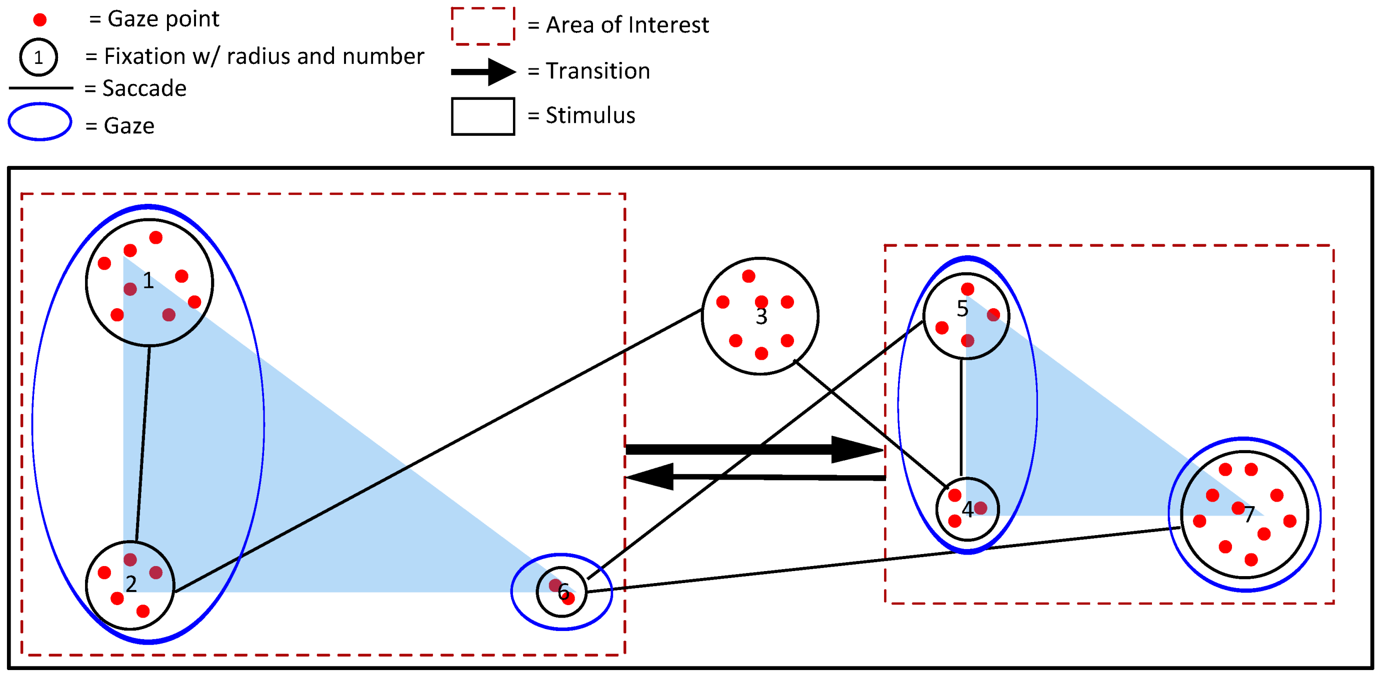


Fig. 1. Gaze points are spatially and temporally aggregated into fixations. Saccades connect fixations and have a certain duration the radius represents. A complete sequence of fixations and saccades is called a scanpath. Areas of Interest (AOIs) are regions of specific interest on a stimulus. Fixations within AOIs are temporally ordered into gazes. A saccade from one AOI to another is called a transition with a transition count.

as recording devices become cheaper and publicly available. Additionally, eye tracking is combined with different data sources, leading to a large amount of different data types (variety), e.g., electroencephalography (EEG) [11], galvanic skin response (GSR), motion tracking, functional magnetic resonance imaging (fMRI), verbal data [12], mouse and keyboard interactions, or personal data from social networks. Kurzhals and Weiskopf [13] discuss the impact of a wider use of eye tracking technology in the context of personal visual analytics of eye movement data. They describe challenges of visual analytics for eye tracking, however, focus on the scenarios like "quantified-self"; in contrast, we emphasize challenges related to big eye-movement data.

Analyzing eye movement data collected during a user study requires established methods. Typically, statistical significance is calculated using different eye movement metrics, i.e., movement measures, position measures, numerosity measures, or latency and distance measures [12]. Additionally, visualization techniques can be used to analyze the data [14]. They are either point-based, e.g. scanpath or attention map visualizations, or AOI-based, e.g. AOI timelines, scarf plots, dwell maps, or transition matrices [12], [14].

Most of these visualization techniques still lack a deeper analysis and combination of different approaches including appropriate interaction techniques. Thus, the use of visual analytics techniques has been investigated for the evaluation of large movement data [15] in general and of eye movement data in particular [16], [17], [18]. However, a detailed analysis how big eye-movement data can be analyzed using visual analytics techniques is missing. We will fill this gap by discussing the challenges of big eye-movement data analysis. Examples from different future scenarios highlight the perspectives this new area might bring and how the challenges could be resolved.

III. Data Model

Different data is collected while the eyes of people are being tracked, either while taking part in an eye tracking study in a laboratory or while solving tasks in the real world. The basic data types as well as the collection of additional data sources is discussed next. Based on the collected data types in eye tracking, the challenges of eye movement data are described in the context of big data.

A. Eye Movement Data

Eye movement data has an inherent spatio-temporal nature. Figure 1 illustrates the different data types of eye movement data: gaze points, fixations, saccades, gazes, areas of interest, transitions, and a stimulus. The different data types are explained in more detail in the following.

Fixations, Saccades, and Trajectories: Eye tracking equipment collects gaze points aggregated into fixation points p_i on a stimulus. Timestamps are attached to fixations, which express when the eye first enters this point (t_{e_i}) and when it leaves the fixation point again (t_{l_i}). This time interval is further denoted as a fixation duration

$$t_{d_i} = t_{l_i} - t_{e_i}$$

The rapid eye movements between two fixations are called saccades. A sequence of fixations can be modeled as a trajectory T, often referred to as scanpath. Each individual trajectory

$$T_k, 1 \leq k \leq m$$

is consequently a sequence of temporally ordered fixations

$$T_k := (p_{k_1}, \ldots, p_{k_n})$$

with $k_n \in \mathbb{N}$. A challenge when comparing trajectories is that the trajectory of each participant can have differently long fixation durations. The number of all $m \in \mathbb{N}$ trajectories is modeled as

$$\mathbb{T} = \{T_1, \ldots, T_m\}$$

Stimuli: A stimulus can either be 2D or 3D and static or dynamic. A dynamic stimulus itself can be modeled as a sequence S of 2D or 3D images F_j, where

$$S = (F_1, \ldots, F_a)$$

with $a \in \mathbb{N}$. Each image

$$F_j,\ 1 \leq j \leq a$$

is shown for a certain amount of time before its content changes, i.e., the frames of a video. For a static stimulus, the same content is shown the whole time ($S = F_1$). The stimulus content may also be changed on users' demand. Walking through a 3D scene, i.e., the real world or a virtual world, generates a sequence of stimuli that are different for each participant. This requires another analysis step using computer vision methods to remap the different images.

Areas of Interest: Areas of interest (AOIs) are regions on a stimulus which are of specific interest for the analysis. AOIs are connected subsets $S_{i,j} \subseteq F_j$ in a stimulus sequence where j denotes the sequence element and i the specific AOI at a certain point in time. Consequently, AOIs can have a time-varying nature, too. AOIs can be defined depending on the semantics of the stimulus, on the hot spots of the recorded data, or naively as an equally sized grid. Fixations within an AOI are temporally aggregated into gazes, sometimes also referred to as dwells. Transitions are saccades, i.e., changes between different AOIs. Using semantic information as AOIs gives additional information about which areas on the stimulus were focused on to understand viewing strategies of participants [19]. With 3D stimuli, the AOIs turn into objects of interest and more geometrical information has to be saved for the analysis [20].

Eye Movement Metrics: Based on the basic eye movement data types (fixations, saccades, gazes, and transitions) various more complex metrics can be defined. For example, number of fixations, saccade direction, amplitude, or length. More metrics can be found in the book by Holmqvist et al. [12]. These data types can further be analyzed by calculating average fixation durations, transition matrices, or the ratio of fixations and saccades. A time-varying behavior of the metric values may also be of special interest. For example, learning effects while inspecting a stimulus can cause a decreasing fixation duration over time.

B. Additional Data Sources

Moreover, data from additional data sources can be collected and evaluated. For example, in classical eye tracking studies qualitative feedback, additional recordings such as mouse or keyboard interaction, or verbal and audio data might be stored. In real-world scenarios, video material of the surrounding environment is recorded as well. Additionally, if data is recorded via smart phones, the data can be synchronized with other data from social networks or web profiles. This can show connections of users to each other. Additionally, groups of people can be found and compared based on their eye movement data. Different sensor data can be collected as well. If smart phones are used, accelerometers could track motions, EEG and GSR could collect data about brain waves, skin response, pulse, or pupil dilation. Eye trackers built into cars could be synchronized with different sensors in the car, e.g., the velocity, steering wheel angle, or the human-car interaction. The additional data has to be synchronized if possible based on timestamps with the eye movement data to analyze it [21].

IV. Challenges for Big Eye-Movement Data Analysis

Since the complexity (volume, velocity, and variety) of eye movement data is increasing, eye tracking can be considered big data. Thus, challenges emerge for newly established analysis tasks and the question arises how this data can be evaluated. Statistics and visualization techniques alone are not useful to find insights in eye movement data from many people, i.e., we need a combination of concepts from the field of visual analytics. Data preprocessing, filtering, or data mining as well as interactive visualizations exploiting the strengths of the human visual system and perceptual abilities become of special interest.

This connection between eye tracking and big data is shown in Figure 2. Eye tracking is approaching big data dimensions. As big data can be analyzed using approaches from the visual analytics domain, eye movement data could also be evaluated with visual analytics techniques. Thus, the question arises how eye movement data can be analyzed using visual analytics methods.

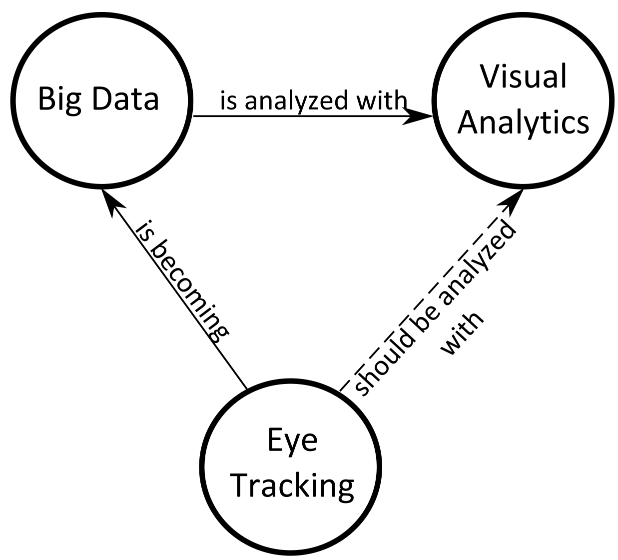


Fig. 2. Big data is analyzed using visual analytics techniques and approaches. Eye movement data is becoming big data. Thus, eye movements should be analyzed with visual analytics approaches as well.

A. Eye Tracking and Big Data

Big data visual analytics is a promising field since it is focused on effectively dealing with ever growing data sets. It is more or less successfully applied to vast amounts of data

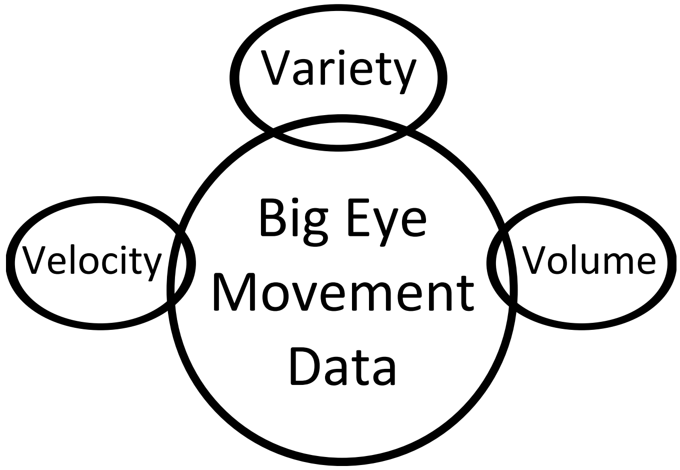


Fig. 3. Big eye movement data consists of the three V's. Variety is the most important and challenging V.

in the fields of health care, science, engineering, finance, and business [3]. In eye tracking research, the growing amount of data is reaching big data dimensions, and the three V's are eventually fulfilled. Especially, the variety is increasing in eye movement data. Thus, it is the most important and challenging of the three V's (cf. Figure 3). The three V's are explained in more detail in the following.

Volume: The amount of data generated in eye tracking studies increases. Recording rates are now up to 500 Hz and more, e.g., the SMI RED500, and precision increases as well. The number of people that can be tracked is raised due to eye tracking in cars or on smart phones. In the future, with crowd sourcing platforms, eye tracking could be conducted with millions of people using their smart phones. And one could imagine that high resolution cameras would be able to track the eyes of everyone, everyday, everywhere making eye tracking publicly available. This would also lead to longer durations, i.e., 24 hours for 365 days of the year, and larger data sets that have to be analyzed.

Velocity: Using smart phones or personal eye tracking glasses, real-time eye tracking is now possible for individuals. This also requires analysis on-line and in real-time. Cheap eye tracking systems can be bought for only $99 [22] and can be used as interaction mechanisms with personal computers.

Variety: A combination with data recorded and measured by other devices such as interaction data, verbal data, EEG, GSR, motion tracking, fMRI, and the like is possible. Such data needs to be synchronized, e.g., by registering timestamps. Additionally, data from groups could be used to enrich the data, e.g., by using data from social networks or web profiles. New analysis and visualization techniques have to be developed to analyze this heterogeneous data.

B. Analysis Tasks

Big eye-movement data can go in two different directions, each having diverse analysis tasks. First, classical laboratory eye tracking studies can become big data and second, new field studies outside the laboratory can be thought of. Each has its own research questions, challenges, and data types. In the following, we describe the two possible directions in more detail.

Eye Tracking User Studies: Classical eye tracking studies are conducted in a laboratory where variables and conditions are closely controlled. Typically, in human-computer interaction or visualization research 20–30 participants and in psychological studies up to 500 participants are tracked and analyzed. With modern low-cost remote eye trackers and smart phones, classical eye tracking studies could be conducted with more participants. If people use eye trackers at home and participate in studies via crowd sourcing, a larger number of participants could be tracked and analyzed. Additionally, remote interactive eye tracking devices have been developed in recent years and have become affordable to users. This allows users to play games on the computer and researchers to collect data. Typical games for interaction with the eyes is to steer a character or whack a mole. These types of studies, where users play a game, while data is gathered and analyzed is a new form of user studies in the large [23]. Letting people track their eyes at home or in their personal environment would lead to an increase in recording times. For example, if eye tracking is conducted in the car, participants could wear personal eye tracking glasses and track themselves during their daily driving. Also, different other data sources besides eye movement data could be gathered. Participants could collect personal information with their smart phone or within their car to enrich the data. If people participate in eye tracking studies from their homes, it would degrade close verification of variables. However, a larger number of participants could compensate this effect. Additionally, weak effects in statistics might be detected more often. Another issue is accuracy, especially when using smart phones for eye tracking. Modern smart phones are too small for a precise recording of the data and typically only top, middle, and bottom of the screen can be distinguished. However, this might change as cameras and algorithms improve.

Real-Time Eye Tracking: A new class of eye tracking tasks is established if eye movement analysis is moved into the real world and out of the laboratory. Field studies are not classical user experiments anymore and we cannot speak of participants in the typical sense. Here, we want real-time data collection and analysis. Depending on the devices used for data collection, we see two possible scenarios: eye tracking using high resolution cameras or public displays, and eye tracking using (virtual/augmented reality) glasses. In either case, people could be tracked and data could be analyzed in real-time based on reactions from large groups. This data could be used to place advertisements, lead attention using large gaze contingent displays [8] to parts on a display of interest, or enrich existing data with the eye movements of people. Tracking people 365 days a year, 24 hours a day, creates large amounts of data and long eye movement sequences per person. Additional data such as web profile information, video data from the surroundings, or the 3D geometry of the world can further enrich this data. Social network data can be used to show dependencies of different people and make, for example, advertisement placement even more personalized. Using virtual or augmented reality, eye tracking glasses would allow one to show these personal advertisements directly as people move in the world, e.g., in a stadium, or while doing their shopping. This new eye movement task has some challenges. First, calibration of eye trackers has to be simple and intuitive as users wear glasses. Even with calibration, eye tracking glasses at the moment have lower sampling rates (30 to 60 Hz) than remote eye trackers. This will lead to uncertain, missing data with errors that has to be considered in the data analysis. High resolution cameras would need to be able to find the eyes of people using computer vision approaches while walking around. Also, cameras have to assure that a person is tracked continuously while multiple cameras follow. Creating personalized advertisement would require an analysis in real-time and situation awareness of algorithms. Additionally, consent from people has to be acquired to allow cameras to track people. Thus, incentives for people to allow this surveillance have to be established, e.g., collecting points, receiving money, discounts, or gifts.

C. Visual Analytics Technology

In eye tracking as well as in big data research, visual analytics methods have been used for analysis. Visual analytics combines methods from data analysis (e.g., clustering, machine learning), human-computer interaction, and visualization. Andrienko et al. [16] and Burch et al. [17] investigated how visual analytics techniques from geographic information systems (GIS) can be applied to eye movement data. The authors found out that not all visual analytics methods from GIS can be used in eye movement research. The difference between movement data in GIS and eye movements is that saccades lead to jumps rather than continuous trajectories.

However, even for big movement data [15] visual analytics approaches exist that can be applied to eye movement data. For example, clustering is an important technique to group information. For eye movement data researchers are typically interested in common behavior of people. Clustering can be used to group eye movement data. Time clustering is in particular useful to understand if there are different strategies depending on the stimulus content when a dynamic stimulus is shown. Understanding if a specific semantic information has an influence on the behavior of a spectator is also relevant.

If algorithmic analysis alone is not sufficient, visualization techniques come into play. For example, in a scenario where a problem cannot be clearly defined for an algorithm to solve, visualization can produce a representation of the data in which visual patterns can be found rapidly using the human visual system. Many visualization techniques for eye movement data have been designed [14], and especially techniques for dynamic and 3D stimuli are of interest, e.g., [24], [25], [26], [27], [28], [29], [30].

However, it is questionable if today's visualization techniques are able to deal with the growing amounts of eye movement data. Big eye-movement data is not only large, its complexity is increasing as additional data sources are being added. Therefore, we need improved machine-based analysis methods that are able to work with the big and complex data, and at the same time, integrate well within a visual analytics system.

Furthermore, for real-time analysis, there should be only little (or even no) visual interaction, requiring a powerful automatic analysis component in the analytics system. However, automatic analysis requires processing of the 3D dynamic stimulus in real-time. This might be achieved if computer vision algorithms improve. At the moment, for example, most AOIs still have to be created manually; this approach is infeasible for large and complex 3D dynamic stimuli.

V. Future Application Scenarios

In this section, we illustrate challenges and perspectives from three application scenarios for the field of automotive industry, sports, and marketing, where each represents aspects of classical laboratory experiments and real-time eye tracking.

A. Eye Tracking During Car Driving

Mobility is one of the challenges in the 21st century. The number of cars is constantly increasing world wide and as a result, traffic on the roads, too. For this reason, driving a car (Figure 4) nowadays during rush hours demands a high cognitive effort. To reduce this effort and to make driving safer and more comfortable, car companies could in the future record eye movements of the car drivers. The analysis of the eye movement behavior helps them to understand how drivers perceive certain traffic situations and to optimize human-car interaction. Eye tracking glasses or stationary systems located in the cockpit would have to record eye movements.

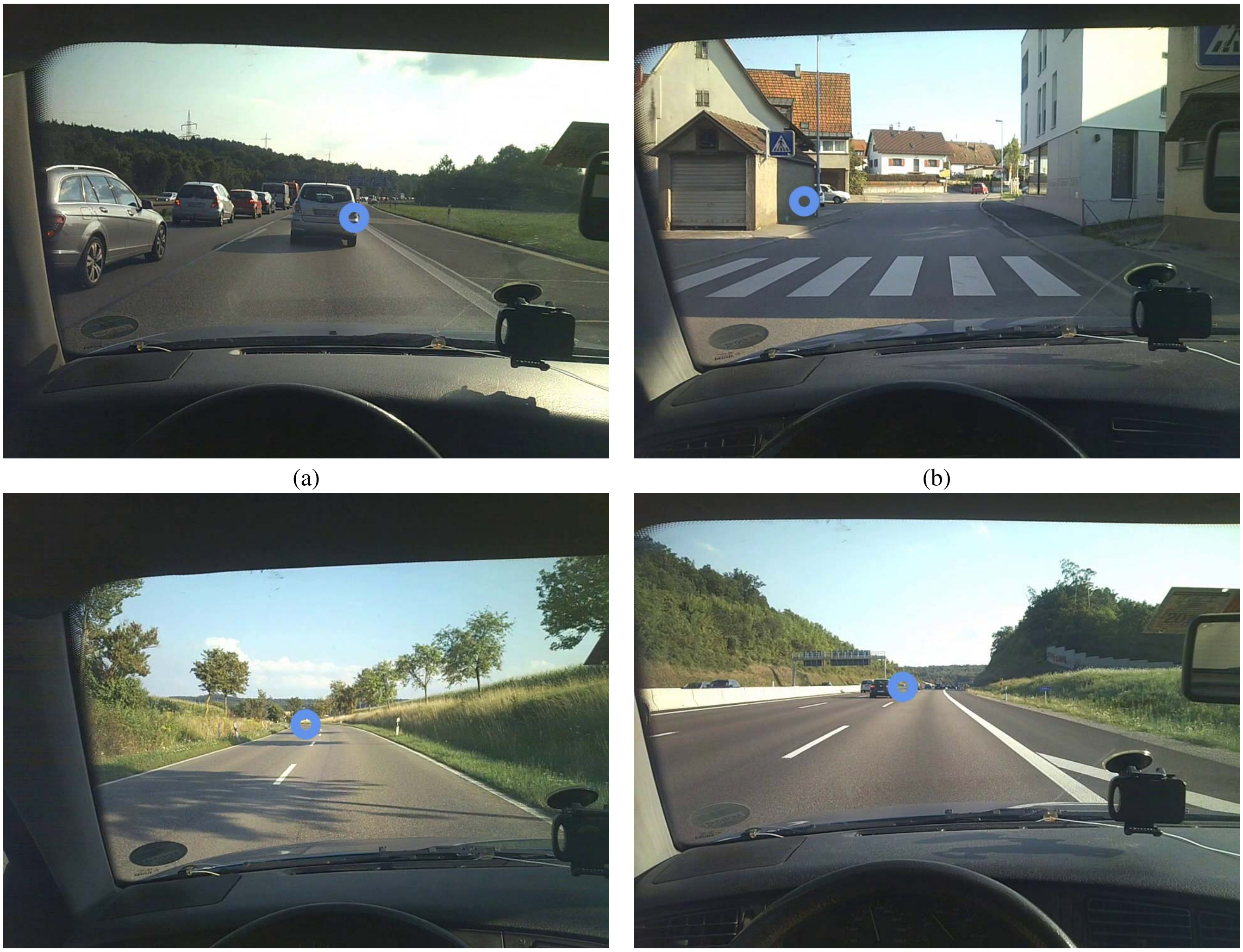
A special characteristic of the data sets recorded in such a scenario is their long time duration, their semantic meaning, and the correlation to physical reactions of the car. If we assumed a duration of one hour while driving a car, the recorded scanpath would consist of approximately $4 \times 60 \times 60 = 14{,}400$ fixations (assuming an average fixation duration of roughly 250 ms). In order to calculate significant statistical results, between 50 and 100 participants must be analyzed as a minimum. This leads to $100 \times 14{,}400 = 1{,}440{,}000$ fixations. Besides recording eye movements, further car information could be used to find correlations between the drivers' perception, their physical reactions, and the state of the car. For example, this additional information could be the GPS location of the car, its velocity, acceleration, braking activity, or steering wheel angle. Based on the GPS location, semantic information about the situation and the environment of the car could also be added during the analysis.

For retrospectively analyzing the scanpaths, the fixations have to be analyzed with respect to the other data streams. Additionally, fixations must be matched with objects in front of the driver. This can be achieved with computational or AOI-based methods. The main idea of this analysis is to find patterns in the eye movement data of one or several drivers, a certain traffic situation causes and results in a physical reaction of the car.

B. Eye Tracking During Sporting Events

Thousands of people are attending sporting events like soccer, basketball, baseball, or rugby. Tracking spectators during a match is a real-world example requiring real-time analysis. For example, reactions of groups could be analyzed or attention could be guided to specific parts of a match using huge gaze-contingent displays. This could be achieved if all spectators were wearing eye tracking glasses or if high resolution cameras captured eye movements during games.

The data collected during such a sporting event would be tremendous. For example, in a soccer stadium of the first German national league an average of 50,000 people are typically



(a) (b) (c) (d)

Fig. 4. Tracking car drivers' eyes produces vast amounts of spatio-temporal data in dynamic 3D stimuli. We can see that the dynamic stimuli content is different from scene to scene, and also from driver to driver. An analysis of the corresponding eye movement data is challenging. Additional data sources can easily be incorporated into the visual analytics process. © 2015 VISUS, University of Stuttgart.

watching a soccer match. For a match lasting 90 minutes, this will lead to approximately $240 \times 90 \times 50{,}000 = 1{,}080{,}000{,}000$ fixations to be recorded. Adding further information about the spectators such as gender, personal preferences, and the like can serve as extra data sources to refine possible findings.

Interesting in this scenario is to take into account the semantic meaning of the displayed stimulus, i.e., the 3D dynamic scene. The general problem in this use case is the time-varying and spatial nature of the data together with calibration errors, uncertain or missing data points, and possible occlusion problems depending on the field of view and perspective of the spectator. Moreover, the scene is inspected at the same time from different perspectives, demanding advanced strategies from the field of computer vision to reproduce the focus of visual attention.

C. Eye Tracking During Shopping

A large department store or supermarket has to deal with thousands of people per day. Consumers are walking around, buying groceries or looking at products. Tracking the eyes of people may give hints about their buying strategies. Finding patterns and insights in this kind of data can be useful for supermarkets to improve their selling strategies. Wearable eye tracking glasses (see Figure 5) could be distributed at the entrance or high resolution cameras could be attached to the shopping carts to track eyes of shoppers. In this scenario, the eye movement data could be analyzed in real-time giving hints about special offers, making suggestions on what to buy, or guiding attention to specific products. This would require a real-time analysis of the data.

The problem in this scenario is that the point of attention typically depends on the semantics of the displayed stimulus which is a 3D scene. However, in this case, the scene can be changed on users' demand: the user is free to decide where to walk in a supermarket and where to look at. Consequently, the content of the scene is dependent on the customer and the shopping task. Also, the number of fixations is different for each spectator. This is the major difference to the soccer scenario in which the presented stimulus is more or less the same for each spectator. The complexity of the task is one

Fig. 5. User wearing eye tracking glasses in a supermarket shopping task.

deciding factor for the duration and consequently, influences the sequence and data set size. The changing stimulus content as well as the differently long eye movements make an analysis of such a data set scenario even more challenging.

VI. Future Challenges

Tracking the eye movements of many (more than 10,000) people gives a vast eye movement data set where additional devices measure additional attributes. The combination and synchronization of all the data sources is a challenging task, in particular when the content of the displayed stimulus is changing over time. This can happen if a single animation or video is shown or if the spectators have an influence on the content. We see several future challenges in the field of eye tracking taking into account hardware and costs, displayed stimuli, users, recorded data and metrics, and privacy issues, see Table I.

- **Hardware & Costs:** The hardware technology is steadily improving. From self-made stationary eye tracking devices in the past to professional and expensive eye tracking glasses as well as low-cost remote eye trackers for interaction purposes, we are moving to an era where smart phones and personal eye tracking glasses will provide an opportunity to track people's eyes. Although, the hardware enhancement is a promising aspect, it also produces larger amounts of data for which the analysis, visualization, and interaction techniques have to be designed in order to keep pace with the hardware technology.
- **Stimuli:** Displayed stimuli are changing from static 2D pictures as in Yarbus' work [31] to dynamic 3D scenes. Moreover, the content of the scenes can be interactively changed on a spectator's demand, requiring more advanced techniques to derive patterns, insights, and finally knowledge from the data.
- **Users:** As illustrated in the future application scenarios, the number of users will increase as well as their expertise. Today, mainly researchers are working with eye tracking systems; however, once the hardware is cheap enough and the user has a real benefit from eye tracking, also non-experts will join the group of users. If the number of users increases and more eyes are tracked, the more reliable statistical evaluation of eye movement data will become.
- **Recorded Data and Metrics:** Starting with fixations and saccades, we are now dealing with smooth pursuits and additional information from the participants as well as input from other sensors and data sources. In the future, taking the semantic information of the displayed stimuli into consideration requires 3D real-world data to be investigated and real-time decisions will be required. This calls for handling uncertainty in the data from errors or missing data due to calibration difficulties or occlusion.
- **Evaluation Methods:** In the early days of eye tracking, visual inspection was used to evaluate data. This process only allowed small datasets to be analyzed. Nowadays, we are generating statistics and use visualization techniques augmented by interaction features to find insights in eye movement data. In the future, more sophisticated visual analytics techniques are needed to overcome the issue of big eye-movement data.
- **Privacy:** If more people's eyes are tracked and more data is collected, privacy and security become issues. The data should not become publicly available and consent by users has to be obtained if the data is analyzed. This requires mechanisms to easily obtain consent if millions of people are tracked.

VII. Conclusion and Future Work

In this position paper, we described challenges and perspectives for big eye-movement data visual analytics. Table I shows a summary of the most important aspects discussed in this paper. Eye tracking devices have changed from self-made low-budget eye trackers, to professional and expensive eye tracking glasses. However, also low-cost remote eye trackers for interaction purposes are being produced and used frequently. In the future, smart phones and personal eye tracking glasses will become a means to track massive amounts of users. Stimuli have changed from 2D static images, to 2D and 3D dynamic stimuli, and the trend is going into the direction of unconstrained real-world scenarios. Also, with eye tracking becoming more widely available, the number of people tracked is changing: from typical numbers of 10 to 500 participants in today's eye tracking studies to possibly 1,000,000 or more people to be tracked in future scenarios. The data recorded is changing in the direction of more and diverse data types being collected, requiring new and advanced analysis techniques for real-time analysis and big data visual analytics techniques. Our three scenarios for future eye movement applications showed which challenges we will be facing in the future and what benefits we could have from massive eye movement data.

TABLE I. THE PAST, PRESENT, AND FUTURE OF EYE TRACKING ACCORDING TO DIFFERENT CATEGORIES.

	Past	Present	Future
Hardware & costs	Stationary eye tracking devices (Self made)	Professional glasses (>$30 000) Low-cost remote eye trackers ($99)	Smart phones and personal eye tracking glasses
Stimuli	2D static stimuli (images)	2D/3D dynamic stimuli (virtual reality, video)	Unconstrained real-world scenarios
Users	<10	10 to 500	>1,000,000
Recorded data and metrics	Fixations and saccades	Video, high-resolution gaze data (smooth pursuits)	Numerous additional data sources
Evaluation methods	Visual inspection	Statistics & Visualization	Big Data Visual Analytics
Privacy	Not an issue	Signed forms	Consent needed

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REFERENCES

[1] J. S. Ward and A. Barker, "Undefined by data: A survey of big data definitions," *CoRR*, vol. abs/1309.5821, pp. 1–2, 2013.

[2] A. De Mauro, M. Greco, and M. Grimaldi, "What is big data? A consensual definition and a review of key research topics," *AIP Conference Proceedings*, vol. 1644, no. 1, pp. 97–104, 2015.

[3] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, and S. U. Khan, "The rise of 'big data' on cloud computing: Review and open research issues," *Information Systems*, vol. 47, pp. 98–115, 2015.

[4] D. Laney, "3d data management: Controlling data volume, velocity, and variety," META Group, Tech. Rep., 2001.

[5] D. A. Keim, F. Mansmann, D. Oelke, and H. Ziegler, "Visual analytics: Combining automated discovery with interactive visualizations," in *Proceedings of 11th International Conference of Discovery Science*, 2008, pp. 2–14.

[6] D. A. Keim, F. Mansmann, J. Schneidewind, J. Thomas, and H. Ziegler, "Visual analytics: Scope and challenges," in *Visual Data Mining – Theory, Techniques and Tools for Visual Analytics*, ser. Lecture Notes in Computer Science, S. Simoff, M. H. Böhlen, and A. Mazeika, Eds. Springer, 2008, vol. 4404, pp. 76–90.

[7] J. Thomas and K. Cook, Eds., *Illuminating the Path*. IEEE Press, 2005.

[8] A. Duchowski, "A breadth-first survey of eye-tracking applications," *Behavior Research Method, Instruments, & Computers*, vol. 34, no. 4, pp. 455–470, 2002.

[9] G. Goth, "The eyes have it," *Communications of the ACM*, vol. 53, no. 12, pp. 13–15, 2010.

[10] M. Raschke, D. Herr, T. Blascheck, M. Burch, M. Schrauf, S. Willmann, and T. Ertl, "A visual approach for scan path comparison," in *Proceedings of the Symposium on Eye Tracking Research & Applications*, 2014, pp. 135–142.

[11] M. Rodrigue, J. Son, B. Giesbrecht, M. Turk, and T. Höllerer, "Spatio-temporal detection of divided attention in reading applications using EEG and eye tracking," in *Proceedings of the 20th International Conference on Intelligent User Interfaces*, 2015, pp. 121–125.

[12] K. Holmqvist, M. Nyström, R. Andersson, R. Dewhurst, H. Jarodzka, and J. Van de Weijer, *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford University Press, 2011.

[13] K. Kurzhals and D. Weiskopf, "Eye tracking for personal visual analytics," *IEEE Computer Graphics and Applications*, vol. 35, no. 4, pp. 64–72, 2015.

[14] T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, and T. Ertl, "State-of-the-art of visualization for eye tracking data," in *EuroVis – STARs*, R. Borgo, R. Maciejewski, and I. Viola, Eds., 2014, pp. 63–82.

[15] N. Andrienko and G. Andrienko, "Designing visual analytics methods for massive collections of movement data," *Cartographica: The International Journal for Geographic Information and Geovisualization*, vol. 42, no. 2, pp. 117–138, 2007.

[16] G. L. Andrienko, N. V. Andrienko, M. Burch, and D. Weiskopf, "Visual analytics methodology for eye movement studies," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, pp. 2889–2898, 2012.

[17] M. Burch, G. L. Andrienko, N. V. Andrienko, M. Höferlin, M. Raschke, and D. Weiskopf, "Visual task solution strategies in tree diagrams," in *Proceedings of IEEE Pacific Visualization Symposium*, 2013, pp. 169–176.

[18] M. Burch, K. Kurzhals, and D. Weiskopf, "Visual task solution strategies in public transport maps," in *Proceedings of the 2nd International Workshop on Eye Tracking for Spatial Research co-located with the 8th International Conference on Geographic Information Science, ET4S@GIScience*, 2014, pp. 32–36.

[19] M. Raschke, T. Blascheck, M. Richter, T. Agapkin, and T. Ertl, "Visual analysis of perceptual and cognitive processes," in *Proceedings of the International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (IVAAP)*, 2014, pp. 284–291.

[20] T. Pfeiffer and P. Renner, "EyeSee3D: a low-cost approach for analyzing mobile 3D eye tracking data using computer vision and augmented reality technology," in *Proceedings of the Symposium on Eye Tracking Research & Applications*, 2014, pp. 369–376.

[21] T. Blascheck and T. Ertl, "Towards analyzing eye tracking data for evaluating interactive visualization systems," in *Proceedings of the Fifth Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization*, 2014, pp. 70–77.

[22] P. Tanisaro, J. Schöning, K. Kurzhals, G. Heidemann, and D. Weiskopf, "Visual analytics for video applications," *it – Information Technology*, vol. 57, no. 1, pp. 30–36, 2015.

[23] M. Pielot, N. Henze, and S. Boll, "Experiments in app stores, how to ask users for their consent?" in *Proceedings of the Workshop on Ethics, Logs and Videotape: Ethics in Large Scale Trials & User Generated Content in conjunction with CHI*, 2011.

[24] K. Kurzhals, F. Heimerl, and D. Weiskopf, "ISeeCube: Visual analysis of gaze data for video," in *Proceedings of the Symposium on Eye Tracking Research & Applications*, 2014, pp. 43–50.

[25] L. Paletta, K. Santner, G. Fritz, A. Hofmann, G. Lodron, G. Thallinger, and H. Mayer, "A computer vision system for attention mapping in SLAM based 3D models," *CoRR*, 2013, arXiv:1305.1163.

[26] L. Paletta, K. Santner, G. Fritz, H. Mayer, and J. Schrammel, "3D attention: Measurement of visual saliency using eye tracking glasses," in *Extended Abstracts on Human Factors in Computing Systems*, 2013, pp. 199–204.

[27] T. Pfeiffer, "Measuring and visualizing attention in space with 3D attention volumes," in *Proceedings of the Symposium on Eye Tracking Research & Applications*, 2012, pp. 29–36.

[28] ——, "3D attention volumes for usability studies in virtual reality," in *IEEE Virtual Reality Workshops*, 2012, pp. 117–118.

[29] S. Stellmach, L. Nacke, and R. Dachselt, "Advanced gaze visualizations for three-dimensional virtual environments," in *Proceedings of the Symposium on Eye Tracking Research & Applications*, 2010, pp. 109–112.

[30] ——, "3D attentional maps: Aggregated gaze visualizations in three-dimensional virtual environments," in *Proceedings of the International Conference on Advanced Visual Interfaces*, 2010, pp. 345–348.

[31] A. L. Yarbus, *Eye Movements and Vision*. Plenum Press, 1967.