

A Task-Based View on the Visual Analysis of Eye-Tracking Data

Kuno Kurzhals, Michael Burch, Tanja Blascheck, Gennady Andrienko, Natalia Andrienko, and Daniel Weiskopf

Abstract The visual analysis of eye movement data has become an emerging field of research leading to many new visualization techniques in recent years. These techniques provide insight beyond what is facilitated by traditional attention maps and gaze plots, providing important means to support statistical analysis and hypothesis building. There is no single “all-in-one” visualization to solve all possible analysis tasks. In fact, the appropriate choice of a visualization technique depends on the type of data and analysis task. We provide a taxonomy of analysis tasks that is derived from literature research of visualization techniques and embedded in our pipeline model of eye-tracking visualization. Our task taxonomy is linked to references to representative visualization techniques and, therefore, it is a basis for choosing appropriate methods of visual analysis. We also elaborate on how far statistical analysis with eye-tracking metrics can be enriched by suitable visualization and visual analytics techniques to improve the extraction of knowledge during the analysis process.

K. Kurzhals (✉) • M. Burch • D. Weiskopf
University of Stuttgart, Allmandring 19, 70569, Stuttgart, Germany
e-mail: Kuno.Kurzhals@visus.uni-stuttgart.de; Michael.Burch@visus.uni-stuttgart.de;
Daniel.Weiskopf@visus.uni-stuttgart.de

T. Blascheck
University of Stuttgart, Universitätsstr. 38, 70569, Stuttgart, Germany
e-mail: Tanja.Blascheck@vis.uni-stuttgart.de

G. Andrienko
Fraunhofer Institute IAIS, Schloss Birlinghoven, 53757, Sankt Augustin, Germany
City University London, London EC1V OHB, United Kingdom
e-mail: gennady.andrienko@iais.fraunhofer.de

N. Andrienko
Fraunhofer Institute IAIS, Schloss Birlinghoven, 53757, Sankt Augustin, Germany
e-mail: natalia.andrienko@iais.fraunhofer.de

1 Introduction

The application of eye-tracking technology as a means of evaluating human behavior has been established in many different research fields [15]. Due to the interdisciplinary constellation of researchers, the specific analysis tasks may also differ between the fields. While one researcher might be interested in the physiological measures (e.g., eye movement speed [27]), another wants to know in what order specific areas of interest on a visual stimulus were investigated [8]. Despite the differences between the research fields, it is possible to derive a high-level task categorization from a data perspective. Since the structure of the recorded data is usually identical in all eye-tracking experiments, we can categorize the analysis tasks according to three main data dimensions and three elementary analysis operations.

Depending on the research question, a statistical analysis of established eye-tracking metrics [23] can be sufficient. However, the more complex the analysis task becomes, the more visual aid is usually required to interpret the data. Regarding the increasing amount of eye-tracking data recorded during experiments [2], it is reasonable to incorporate visual analytics techniques that combine automatic data processing with interactive visualization [1] into the analysis process.

As a starting point, the analysis of eye-tracking data is usually supported by some basic visualization techniques. For statistical measures, the application of statistical plots depicting the changes of a variable over time can already be helpful to interpret the data. In these cases, the visual stimulus is neglected. If the visual stimulus is important for the analysis, additional visualization techniques are usually included in the software suites of the major eye-tracking vendors.

For many years, gaze plots and attention maps (Fig. 1) were (and still are) the most popular visualizations that include information about the underlying visual stimulus. However, not all analysis tasks are facilitated by these techniques. For example, even though animated versions of the techniques in Fig. 1 exist, it is hard to interpret changes over time by simply replaying the animation [46]. Therefore, many new techniques have been developed over the last years to address this and

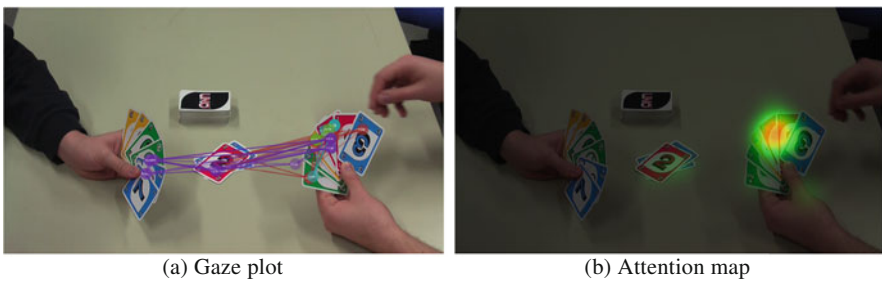


Fig. 1 Typical eye-tracking data visualizations: The (a) gaze plot and the (b) visual attention map are the most common depictions of recorded gaze data

many other analysis tasks, summarized by Blascheck et al. [4]. Additionally, as a beneficial but also challenging aspect, apart from the pure eye movement data a wealth of additional data sources can be integrated into an experiment [2]. Such a collection of heterogeneous data sources often impairs a combined analysis by statistical means and makes a visual approach indispensable.

With that said, our goal is twofold: We define typical analysis tasks when visualization techniques for eye movement data come into play. Our high-level categorization is based on data dimensions directly focusing on recorded eye movement data but also on basic analysis operations. As a second goal, we discuss for each task category to which degree statistical and visual analysis can be applied to perform the given task, and present the suitable techniques. We base the list of examined visualization techniques on the collection provided in the state-of-the-art report by Blascheck et al. [4], which we consider fairly complete.

The overarching intention of this article is to support analysts working in the field of eye tracking to choose appropriate visualizations depending on their analysis task.

2 The Eye-Tracking Visualization Pipeline

We formulate the way from conducting an eye-tracking experiment to gaining insight in the form of a pipeline (Fig. 2) that is an extended version of the generic visualization pipeline [11, 21]. The acquired data consisting of eye movement data and complementary data sources is processed and optionally annotated before a visual mapping, creating the visualization, is performed. By interacting with the data and the visualization, two loop processes are started: a foraging loop to explore the data and a sensemaking loop to interpret it [36], to confirm, reject, or build new hypotheses from where knowledge can be derived. Since the analysis task plays an

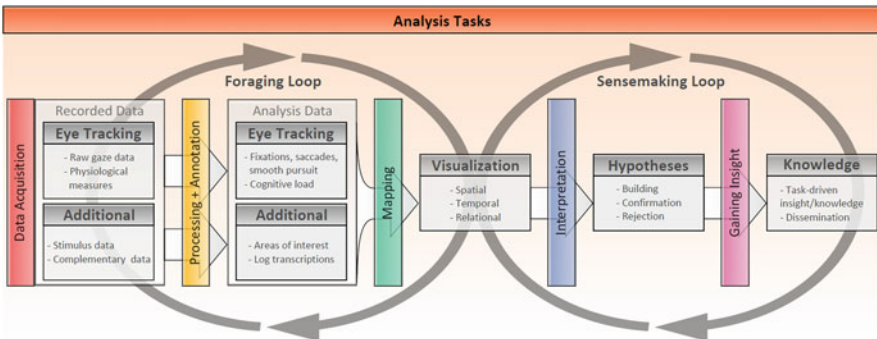


Fig. 2 Extended visualization pipeline for eye-tracking data: The recorded data passes multiple transformation steps before knowledge can be extracted. Each step from data acquisition, processing, mapping, interpretation, to gaining insight is influenced by the analysis task

important role in all steps of the pipeline, we first discuss the underlying data and how it is processed before we introduce our categorization of analysis tasks.

2.1 Data Acquisition

Eye movement data combines several data dimensions of spatio-temporal nature. We distinguish between dimensions directly stemming from the recording of eye movements (raw gaze, physiological measures) and additional data sources serving as complementary data that can help achieve more reliable analysis results when combined with eye movement data. Typically, the displayed stimuli are an additional data source that can usually be included in the analysis process, since they are the foundation of most experiments anyway. Additional data sources provide complementary data such as verbal feedback, electroencephalography (EEG) data, and key press protocols.

The analysis task, or more precisely, the research question, typically defines how the experiment is designed and which data will be recorded. Most scenarios predefine also the visual stimulus. Exceptions are, for example, “in-the-wild” experiments with mobile eye tracking where it becomes much more difficult to control the experiment parameters.

2.2 Processing and Annotation

From the time-varying sequence of raw gaze points, more data constructs can be derived in a processing step. We identified fixations, saccades, smooth pursuits, and scanpaths as the most important data constructs [23]. In this processing step, automatic data-mining algorithms can be applied to filter and aggregate the data. Clustering and classification are prominent processing steps: For example, raw gaze points can be clustered into fixations and labeled. As another example, the convex hull of a subset of gaze points can be extracted to automatically identify areas of interest (AOIs). In general, the annotation of AOIs plays an important role in this step.

From the visual content of a stimulus (e.g., a picture or a video), AOIs can be annotated, providing semantic interpretation of the stimulus. With this information, additional data such as transition sequences between AOIs can be derived. Therefore, analysts can either rely on automatic, data-driven approaches to detect AOIs, or define them manually. Basically, there are two approaches: either defining areas or objects by bounding regions on the stimulus and calculating hits with the gaze data, or labeling each fixation individually based on the investigated content. Especially for video sequences, this annotation is a time-consuming step that often takes more effort than the rest of the analysis process.

From the additional data sources, recorded protocols and log files can typically be derived. It should be noted that each additional data source requires a synchronization with the recorded eye movement data, which can be difficult considering different sampling rates and irregularly sampled data (e.g., think-aloud comments) [3]. The processed data can finally be used for the mapping to a visual representation.

The analysis task influences what filters are applied to the data and what AOIs are annotated. For explorative scenarios in the context of visual analytics, visualization and processing are tightly coupled in a foraging loop, where the analyst can identify relevant data artifacts through interaction with the visualization.

2.3 Mapping

The mapping step projects the analysis data to a visual representation. According to Blascheck et al. [4], the main categories of state-of-the-art visualization techniques for eye tracking are spatial, temporal, and relational data representations. Therefore, our task categorization follows a similar scheme and appropriate visualizations are selected according to the main data dimension that is required to perform the corresponding task. It may be noted that only a few visualization techniques for eye movement data also take into account the additional data sources for an enhanced visual design in order to explore the data. We think that this is actually noteworthy since those data sources may build meaningful input for sophisticated data analyses if they are combined with the traditional eye movement data.

As mentioned before, the analysis task plays the most important role for the choice of the appropriate visualization technique. In the foraging as well as the sensemaking loop, the visualization has to convey the relevant information and should provide enough interaction supported by automatic processing to adjust the visualization to the specific needs of a certain analysis task.

2.4 Interpretation

For the interpretation of the visualization, we can distinguish between two strategies: Applying visualization to support statistical measures and performing an explorative search. In the first case, hypotheses are typically defined before the data is even recorded. Therefore, inferential statistics are calculated on appropriate eye-tracking metrics, providing p -values to either support or reject hypotheses. Here, visualization has the purpose to additionally support these calculations. In the second case, the explorative search, hypotheses might be built during the exploration process.

Filtering and re-clustering data, adjusting the visual mapping and reinterpreting the visualization can lead to new insights that were not considered during the data

acquisition. This explorative approach is particularly useful to analyze data from pilot studies. Building new hypotheses, the experiment design can be adjusted and appropriate metrics can be defined for hypothesis testing in the final experiment.

The interpretation of the data strongly depends on the visualization. With a single visualization, only a subset of possible analysis tasks can be covered. For an explorative search where many possible data dimensions might be interesting, a visual analytics system providing multiple different views on the data can be beneficial. It allows one to investigate the data in general before the analysis task is specified.

2.5 Gaining Insight

As a result of the analysis process, knowledge depending on the analysis task is extracted from the data. As discussed before, this knowledge could be insights that allow the researchers to refine a study design or conduct an entirely new experiment. In the cases where visualization has the main purpose to support statistical analysis, it often serves as dissemination of the findings in papers or presentations. In many eye-tracking studies, this is typically the case when inferential statistics are performed on eye-tracking metrics and attention maps are displayed to help the reader better understand the statistical results.

3 Categorization of Analysis Tasks

The visualization pipeline for eye-tracking data (Fig. 2) shows the steps in which analysis tasks play an important role. For the experienced eye-tracking researcher, the first two steps—*data acquisition* and *processing*—are usually routine in the evaluation procedure. In the context of our chapter, *mapping* is the most important step in which the analysis task has to be considered. When the analysis task is clear, the chosen visualization has to show the relevant information. In this section, we present a categorization of analysis tasks that aims at helping with choosing appropriate visualizations. We discuss the main properties of the involved data constructs, typical measures for these questions, and propose visualizations that fit the tasks.

To provide a systematic overview of typical analysis tasks, we first derive the three independent data dimensions in eye-tracking data:

- **Where?** For these tasks, space is the most relevant data dimension. Typical questions in eye-tracking experiments consider where a participant looked at.
- **When?** Tasks where time plays the most important role. A typical question for this dimension is: when was something investigated the first time?

- **Who?** Questions that investigate participants. Typical eye-tracking experiments involve multiple participants and it is important to know who shows a certain viewing behavior.

With these three independent dimensions, visualizations can be applied to display dependent data constructs (e.g., fixation durations). Since many visualization techniques may not be restricted to just one of these dimensions but may facilitate different combinations of them, we focus our subsections on techniques where the name-giving dimension can be considered as the main dimension for the visualization.

Additionally, we can derive general analytical operations that can be related to other taxonomies (e.g., the knowledge discovery in databases (KDD) process [17]):

- **Compare:** Questions that consider comparisons within one data dimension.
- **Relate:** Questions that consider the relations between data dimensions and data constructs.
- **Detect:** Questions about summarizations and deviations in the data.

This categorization is based on the survey by Blascheck et al. [4], the work of Andrienko et al. [1], and the work of Kurzhals et al. [29]. The authors provide an overview of current state-of-the art visualization and visual analytics approaches for the analysis of eye-tracking data. However, they did not include a discussion of the typical analysis tasks performed with the visualization and visual analytics techniques. The proposed metrics are derived from Holmqvist et al. [23].

3.1 *Where? – Space-Based Tasks*

Typical questions that consider the spatial component of the data are often concerned with the distribution of attention and saccade properties. Statistical measures such as standard deviations, nearest neighbor index, or the Kullback-Leibler divergence provide an aggregated value about the spatial dispersion of gaze or fixation points. If we define a saccade as a vector from one fixation to another, typical *where* questions can also be formulated for saccade directions. If AOIs are available, measures such as the average dwell time on each AOI can be calculated and represented by numbers or in a histogram.

If the stimulus content is important for the analysis, attention maps [7] and gaze plots are typically the first visualizations that come to mind. Attention maps scale well with the number of participants and recorded data points, but totally neglect the sequential order of points. With an appropriate color mapping and supportive statistical measures, an attention map can already be enough to answer many questions where participants looked at, if the investigated stimulus is static.

Space-based tasks for dynamic stimuli, such as videos and interactive user interfaces, require a visualization that takes the temporal dimension into account

considering also the changes of the stimulus over time. If AOIs are available, we refer to the next section, because in this case, *when* and *where* are tightly coupled. In an analysis step before the annotation of AOIs, there are two visualizations techniques that depict *where* participants looked at over time. Those are namely the space-time cube [32, 34] (Fig. 3a) and the gaze stripes [31] (Fig. 3b).

In a space-time cube, the spatial dimension of the stimulus is preserved, while the temporal data is included as a third dimension. Gaze points as well as scanpaths can be investigated over time. Common viewing behavior as well as outliers (Sect. 3.6) can be detected, but the stimulus is usually only available on demand, for example, by sliding a video plane through the space-time volume. Similar representations for one spatial and the temporal dimension are also possible (e.g., de Urabain et al. [13]). Gaze stripes preserve the information about the watched stimulus content by creating small thumbnails of the foveated region for each time step and placing them on a timeline. With this approach, individual participants can be compared. However, the spatial component is in this case implicitly coded by the image content, providing more of an answer to the question what was investigated.

3.2 *When? – Time-Based Tasks*

Eye movement data has a spatio-temporal nature often demanding for a detailed analysis of changes in variables over time. Questions in this category typically have the focus on a certain event in the data (e.g., a fixation, smooth pursuit) and aim at answering when this event happened. Considering the detection of specific events over time, many automatic algorithms can be applied to identify these events. Automatic fixation filtering [41], for example, calculates when a fixation started and ended. For semantic interpretations, combining data dimensions to answer questions *when* was *what* investigated, the inclusion of AOIs is common. For statistical analysis, measures such as the “time to first hit” in an AOI can be calculated.

Without AOI information, the visual analysis of the temporal dimension is rather limited. Statistical plots of variables such as the x- and y-component [19], or acceleration of the eye can provide useful information about the physiological eye movement process. However, combined with the semantic information from AOIs, visualizations help us better understand when attention changes appeared over time.

Timeline visualizations are a good choice to answer questions related to this category. Figure 4 depicts an example where multiple timelines for different AOIs are stacked on top of each other [12, 30]. Colored bars on the timelines indicate when an AOI was visible. Alternatively, this binary decision could also be applied to depict whether a participant looked at the AOI, or not [44, 47]. In Fig. 4, the data dimension *who* was included by displaying histograms inside the bars indicating how many participants looked at the AOI over time. In general, timeline representations depict an additional data dimension or construct, allowing one to combine the data relevant for the analysis with its temporal progress.

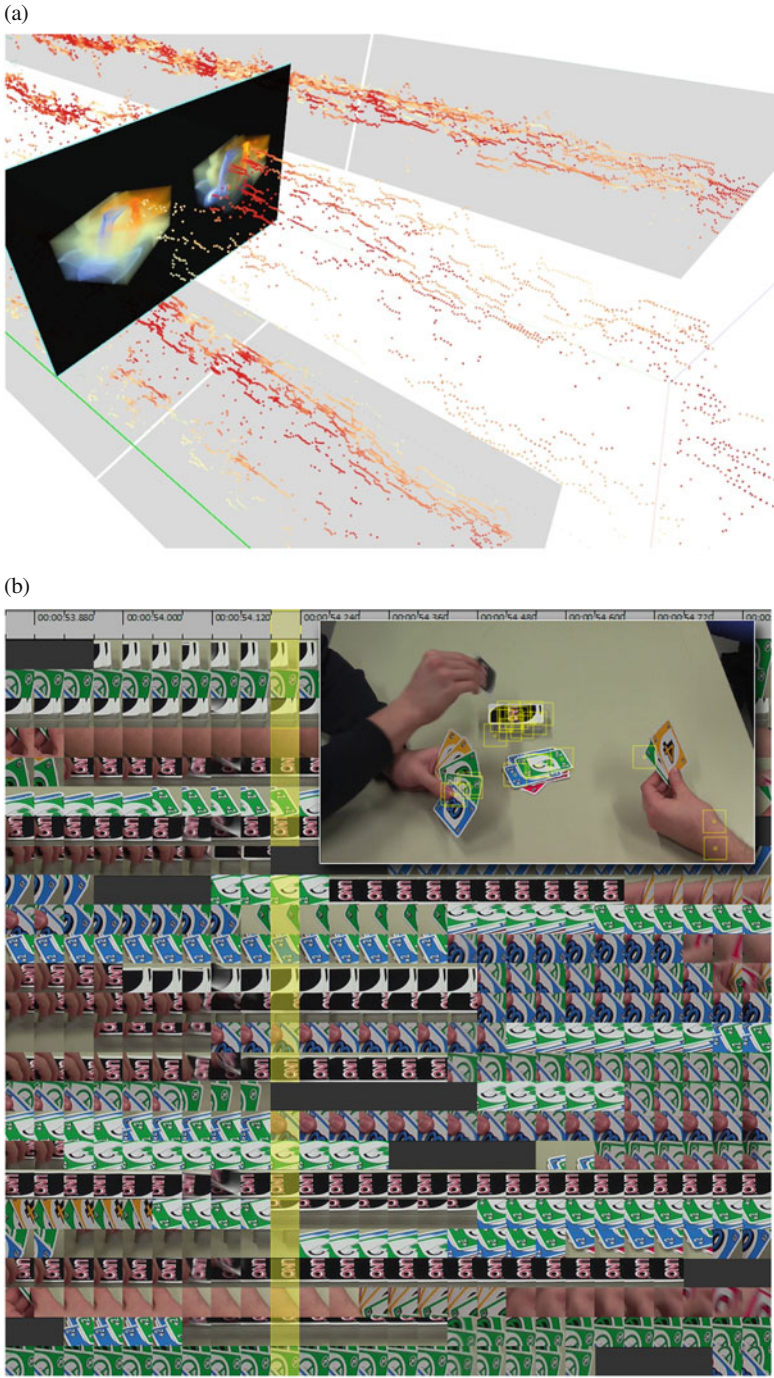


Fig. 3 Two visualization techniques to investigate where participants looked at over time in dynamic stimuli without the need of annotating AOIs. (a) Space-time cube. (b) Gaze stripes

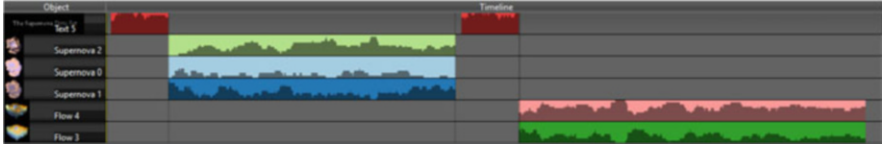


Fig. 4 Timeline visualization showing when an AOI appeared (colored bars) and how many participants looked at it over time (histograms inside the bars)

3.3 Who? – Participant-Based Tasks

Typical questions raised when looking at recorded participants' data can be categorized into those concerning only a single individual or a larger group of people. Inspecting the viewing behavior of participants can provide insights into the visual task solution strategies applied by them (e.g., Burch et al. [8]). For a single participant, a traditional gaze plot is useful to interpret the scanpath, assuming that the recorded trajectory is not too long nor located in just a small stimulus subregion. Generally, most visualization techniques for multiple participants work fine also for an individual participant. For the comparison of multiple participants, gaze plots are less scalable, because of the massive overplotting that occurs when many participants' scanpaths are displayed in one representation.

To ease the comparison of scanpaths, specific metrics to identify similarities between participants can be applied, such as the Levenshtein or Needleman-Wunsch distance [16, 48]. Based on visited AOIs, a string is derived that can be compared by the mentioned similarity measures. As a consequence, scanpaths from many participants can be compared automatically. To interpret the comparison results, a visual representation of the scanpaths that supports the similarity measure can be helpful.

Similar to the concept in Fig. 4, a timeline for individual participants can be created, commonly known as scarf plot [30, 39]. The corresponding color of an AOI is assigned to each point in time it was visited. With a hierarchical agglomerative clustering on the similarity values, a dendrogram can display the similarities between participants. In Fig. 5, participant 4 and 7 are most similar because their sequences of visits to the green and the dark blue AOI shows the highest level of resemblance. Alternatively, one timeline per AOI can be kept and the scanpath can be plotted as a connected line over the timelines [37, 38].

The comparison of participants nowadays benefits from the automatic processing of scanpath similarities. Since the applied similarity measures can lead to different results, a visual interpretation is crucial to avoid misinterpretations.

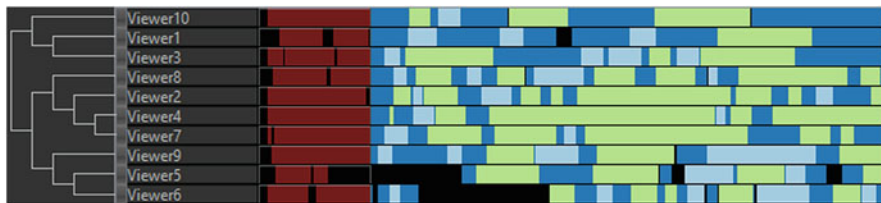


Fig. 5 Timelines for individual participants (scarf plots) depicting their scanpath based on the colors of visited AOIs (*right*). The dendrogram (*left*) displays the hierarchical clustering of the most similar scanpaths, measured by the Levenshtein distance

3.4 Compare

Section 3.3 introduced the comparison of participants based on scanpath similarities. Comparison in general can be seen as one of the elementary analysis operations performed during the evaluation of eye-tracking experiments. In fact, statistical inference is typically calculated by comparing distributions of a dependent variable. For example, fixation durations between different stimulus conditions can be compared with an ANOVA to find out whether a significant difference between the two distributions exists. However, inferential statistics can only provide the information that a difference exists. To interpret the difference between the conditions, a visual comparison is usually a good supplement to the statistical calculations.

Comparison tasks are typically supported by placing several of the visualized data instances next to each other in a side-by-side representation, sometimes denoted as small multiples visualization. Each data instance is visually encoded in the same visual metaphor to facilitate the comparison.

An example of such visual comparison can be found in a seminal eye-tracking experiment conducted by Yarbus [49], with participants investigating the painting “The unexpected visitor”. To compare the viewing behavior for different tasks, the resulting eye movement patterns were depicted by rudimentary gaze plots, allowing an easy interpretation of how the task influenced the eye movements. This visualization strategy can be applied to many techniques, for example, to compare investigated stimulus content over time (Fig. 3b), different distributions of attention on AOIs [9, 12] (Fig. 4), and the comparison of participants [30, 38] (Fig. 5).

A more direct and supportive way to perform comparison tasks is by the principle of agglomeration. In this concept, two or more data instances are first algorithmically compared (e.g., by calculating differences) and then the result is visually encoded in a suitable visual metaphor. Although this technique has many benefits concerning a reduction of visual clutter and number of data items to be displayed, it comes with the drawback of deleting data commonalities that might be important to visually explore and understand the data instances to be compared.

An example of such a scenario is the calculation of differences between attention maps. Attention maps represent a distribution of attention and can be subtracted from each other, leaving higher differences between the values where the

distribution was different. The result can again be visualized as an attention map, showing hot spots in the difference regions.

3.5 *Relate*

In most analysis scenarios, not only a single dimension such as space, time, or participants is in the research focus. A combination of two, three, or even more dimensions and data constructs is included in the analysis to explore the data for correlations and relations between the data dimensions.

Correlations between data dimensions in eye-tracking research are often analyzed statistically. If multiple data dimensions are investigated simultaneously, we typically speak of multivariate data. In a statistical analysis, such multivariate correlations are often evaluated using Pearson's correlation coefficient. It tests how data constructs correlate with each other and how strong this relation is. However, without visual interpretation, correlation values can be hard to interpret. This can be overcome using visualization techniques for multivariate data. Typical examples are scatter plots, scatter plot matrices, or parallel coordinates [22, 24]. Scatter plots have been used in eye movement research for years. For example, Just and Carpenter [25] depicted different metrics such as number of switches, angular disparity, response latency, or duration to investigate cognitive processes. To our knowledge, parallel coordinates have not been used to analyze multiple eye movement metrics so far. However, they could give valuable insights into correlations amongst metrics.

Investigating relations between AOIs or participants is the second important aspect for analysis tasks in this category. The relationship amongst participants has already been discussed in Sect. 3.3. The relationship between AOIs is discussed in the following. Relations between AOIs are often investigated by transitions between them. They can show which AOIs have been looked at in what order. A standard statistical measure is the transition count. Transition matrices or Markov models can give valuable insight into search behavior of a participant [23]. The transition matrices can be extended by coding transition count with color [18], allowing one to detect extrema between AOI transitions efficiently (see Fig. 6a). Blascheck et al. [5] use such transition matrices with an attached AOI hierarchy to show clusters between different AOI groups. Similar to transition matrices, recurrence plots [14] (Fig. 6b) depict the return to fixations or AOIs and thus search behavior of a participant.

Another typical technique for showing relations between elements are graphs and trees. These visualization techniques can be extended to AOI transitions. A transition graph depicts AOIs, or meta information about AOIs (Fig. 6c) as nodes and transitions as links [6, 35]. The example depicted in Fig. 6c is the work of Nguyen et al., which is described in detail in their chapter [35] later in this book. Graphs can be used to represent which AOIs have been focused on and how often. Fig. 6d shows a transition graph where AOIs are depicted as color-coded circle segments. The color corresponds to the dwell time of an AOI. The transitions

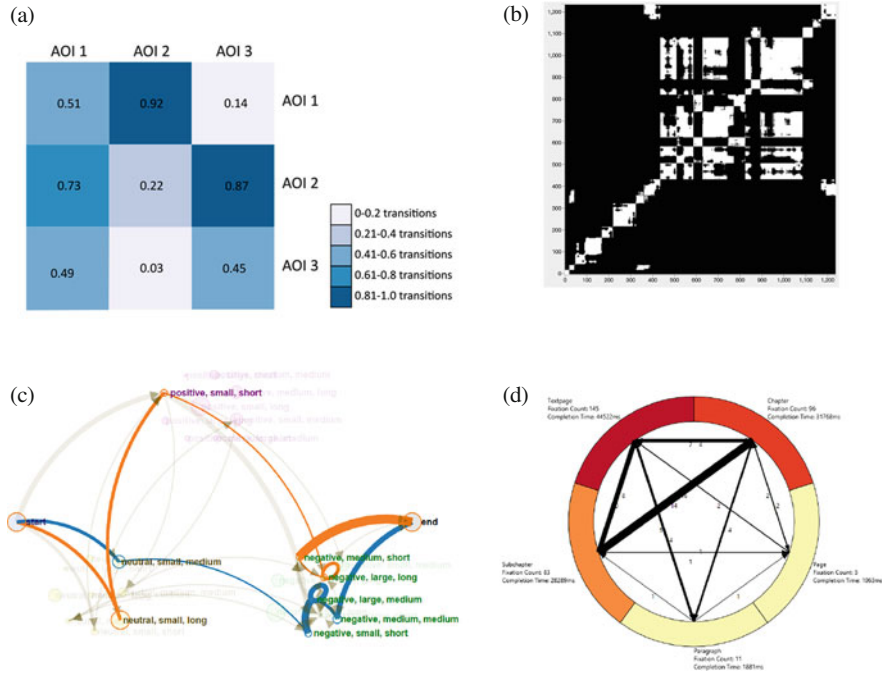


Fig. 6 Visualization techniques to investigate relations in eye-tracking data. (a) Transition matrix. (b) Recurrence plot (with kind permission from Demiralp et al. [14]). (c) State graph (with kind permission from Nguyen et al. [35]). (d) Circular transition graph

between AOIs are shown as arrows where the thickness corresponds to the transition count. Trees are typically used to depict the sequence of transitions [5]. These trees can also be used to visually compare the sequences of different participants and depict common strategies in a visual form [33, 45, 48].

3.6 Detect

Detecting patterns of common viewing behavior is important and often achieved by summarization or aggregation of the data. Such summarizations can also be applied to find outliers in the data which might either result from a problem of the hardware or from unexpected and potentially interesting behavior of a participant.

Descriptive statistics are often applied to achieve this goal. Calculating the average fixation duration, the variance of saccade amplitudes, or the mean scanpath length are some examples. Box plots are typically used to represent these values and additionally depict outliers as a simple-to-understand graph. However, more sophisticated visualization techniques can be utilized to summarize the eye movement data and detect outliers visually.

As mentioned before, summarization visualizations provide a first overview of the data. Summaries can be created for the raw data points, for aggregated data using AOIs, or for the participants. An overview of the point-based data can be visually represented by the fixation coverage displayed on top of the stimulus [10]. This technique allows one to see which parts of the stimulus have been looked at or not. Another possibility is to depict one dimension of the fixation position plotted against time [19]. This allows investigating the general scanning tendency of a participant. Other overview visualizations for point-based data have been described in the previous sections and include the space-time cube (Fig. 3a) and the attention map (Fig. 1b).

Some visualizations are especially designed, or suitable, for detecting outliers and deviations in the data. A visual method for analyzing raw eye movement data can be used to investigate if the raw data is inaccurate or incomplete [42]. Outliers in the recorded, as well as in the processed, analysis data can be identified using visualizations that represent the eye movements in a point-based fashion. Here, timeline visualizations [19, 20, 31] showing one data dimension over time can be applied.

An AOI view facilitates a simple summarization of eye movement data on the basis of AOIs. Here, AOIs are depicted on top of the stimulus and are color coded based on a measure (e.g., gaze duration) [5, 40]. This allows us to analyze how often and which AOIs have been looked at, keeping the spatial context of the AOI on the stimulus. Another technique is to depict AOI rivers [9] (Fig. 7), which represent AOIs on a timeline and where the thickness of each AOI river shows the number of gazes as well as outgoing and incoming transitions.

AOIs may also be used to find deviations in the data. For example, an AOI may not have been looked at during the complete experiment by one or multiple participants. This may be an indicator that the AOI was not needed to perform the experiment task or participants missed important information to perform the task. AOI timelines can help answer this question (Fig. 4). As discussed in Sect. 3.4, presenting AOIs next to each other [26, 37] allows a direct comparison to inspect which AOIs have been looked at or not. Furthermore, individual participants may display a different strategy, which can be found when matching participants using scanpath comparison (Sect. 3.3).

4 Example

In this section, we provide a concrete example of how the discussed analysis tasks relate to eye-tracking data. Our example dataset comes from the benchmark provided by Kurzhals et al. [28]. The video shows a 4×4 memory game where the cards are pairwise flipped until all matches are discovered. Participants ($N = 25$) were asked to identify matching cards by watching the video. Figure 8 shows the stimulus and different methods to visualize the recorded gaze data.



Fig. 7 AOI rivers that show the distribution of attention on different AOIs (colored streams) and transitions between them over time

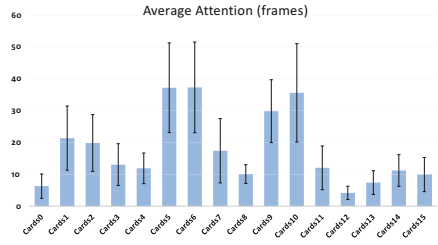
First, we assume that no information about AOIs is available. According to our pipeline (Fig. 2), the recorded gaze data can be processed by fixation detection algorithms, providing analysis data solely based on gaze information. At this early stage in the analysis process, we could apply established eye-tracking metrics (e.g., average fixation count and saccade length) to derive general information of how the participants watched the stimulus video. This kind of analysis would be typical for tasks in the categories *relate* and *compare*.

Attentional synchrony [43] is a specific behavior that occurs during the investigation of dynamic stimulus content. It describes timespans when the majority of participants spent their attention on a specific region, which is often an effect of motion as an attention-guiding feature. Identifying attentional synchrony concerns the categories *when*, *where*, and *detect*. With a space-time cube visualization (Fig. 8d), it is possible to *detect* timespans of attentional synchrony in the spatio-temporal context of the stimulus, meaning that it is quite easy to identify *when* many participants looked at the same region (*where*). In our example, this is typically the case when a new card is flipped, drawing the attention of almost all participants in expectation of the new card image.

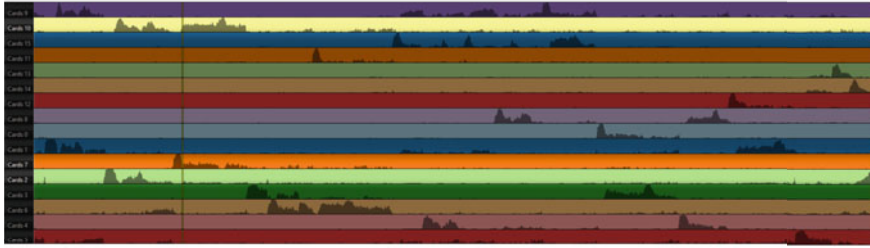
To this point, the statistical, hypothesis-driven analysis of the recorded data can be interpreted as a linear process where metrics are applied and the results are reported. Complementary, in an interactive visualization such as the space-time cube, the data can be clustered and filtered to explore the dataset and identify events of potential interest for new hypotheses. With these possibilities of interacting with the data, the foraging and sensemaking loops (Fig. 2) are initiated.



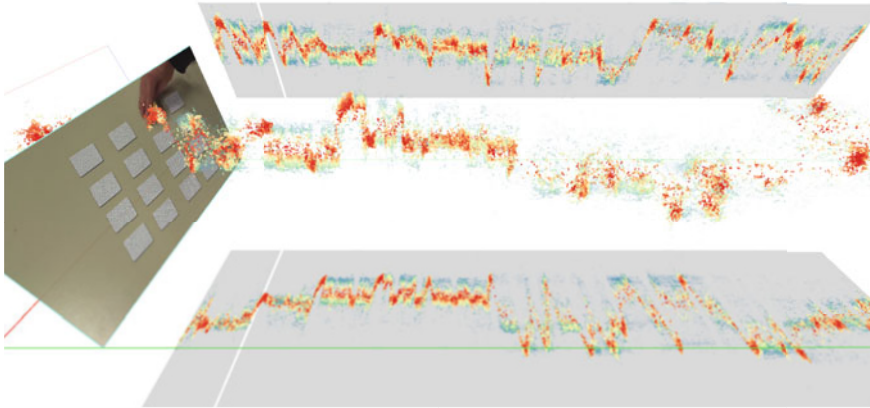
(a) Memory stimulus containing 16 cards that are flipped until all pairs are discovered



(b) Average number and standard deviation of frames with gaze data inside the AOIs



(c) AOI timelines for all cards, indicating when a card was investigated



(d) Space-time cube visualization showing spatio-temporal context of attentional synchrony

Fig. 8 Example of eye-tracking analysis for a video stimulus: **(a)** The video is annotated with AOIs, **(b)** descriptive statistics can be applied to investigate the distribution of attention, **(c)** AOI timelines show detailed information about the temporal distribution, and **(d)** a space-time cube provides spatio-temporal context

In many eye-tracking experiments, the annotation of AOIs, as an additional source for data analysis, is performed. In our example, each individual card represents an AOI (Fig. 8a). With this additional information, hit detection between gaze points and the AOI shapes can be performed to compare the distribution of attention between AOIs (Fig. 8b). As described above, these aggregated metrics

provide an overview, but due to the lack of temporal information, analysis questions considering *when* something happened cannot be answered. To get an overview of the distribution of attention over time, individual timelines for each AOI can be applied (Fig. 8c). The histograms indicate how many participants looked at an AOI at specific points in time. For example, it becomes quite obvious which two cards were flipped in one turn: their corresponding timelines show high values simultaneously. Another example are peaks for single AOIs, indicating attentional synchrony with a focus on the *when* aspect.

Considering the *who* questions, scarf plots could be applied to visualize the AOI sequences of individual participants. Similarity measures between AOI sequences can lead to insights considering different participant groups. As an example, Kurzhals et al. [31] discuss the event when the first matching pair of cards (Card 7 and Card 10) was visible for the first time (vertical line in Fig. 8c). In the turn before this event, Card 2 and Card 10 were flipped. After all cards are covered again, Card 7 is flipped. From this specific point in time, three different viewing patterns can be identified: (1) a group of participants stays on Card 7, possibly trying to remember the position of the matching card; (2) the majority of participants immediately looks at Card 10, where the matching card is; (3) some participants also look at Card 2, indicating problems to remember which card matches. Using a scarf plot visualization, it is possible to identify which participants belong to the identified groups of similar behavior (*detect*). Furthermore, it is possible to apply visualization techniques considering *relate* questions. A transition matrix, for example, could indicate how well individual cards were remembered, i.e., by high transition counts from an AOI to the matching AOI.

In summary, this example provides only a glimpse into possible analysis tasks and applicable visualization techniques that can be covered with the proposed categorization scheme. Based on our example, it also becomes obvious that many eye-tracking related analysis tasks are compositions of the categories and could be solved with different techniques. Therefore, our book chapter wants to provide a guide of possibilities, rather than dogmatic solutions.

5 Conclusion

We have adopted a task-oriented perspective on visualization and visual analysis of eye-tracking data. We have derived a task taxonomy for eye movement data visualization based on a literature research of such visualization approaches, corresponding case studies, and user evaluations. Furthermore, the taxonomy is related to our pipeline of eye-tracking visualization that includes data acquisition via recordings during eye-tracking experiments, processing and annotation of that data, and visualization, finally leading to descriptions and examination of hypotheses and building new knowledge.

One aspect of the task taxonomy adopts the fundamental characteristics of the most important data dimensions in gaze recordings: space (where?), time (when?),

and participant (who?). These data-oriented tasks are complemented by another class of tasks covering analytical operations: compare, relate, and detect. For all tasks, we provide references to representative visualization techniques. In this way, our chapter is meant as a starting point for choosing appropriate methods of visual analysis for the problem at hand. It should be noted that our discussion of previous work does not target comprehensiveness. A systematic review of the literature on eye-tracking visualization can be found elsewhere [4].

Acknowledgements This work was partially supported by the German Research Foundation (DFG) within the Cluster of Excellence in Simulation Technology (EXC 310) at the University of Stuttgart. This work was supported in part by EU in projects datAcron (grant agreement 687591) and VaVeL (grant agreement 688380).

References

1. Andrienko, G.L., Andrienko, N.V., Burch, M., Weiskopf, D.: Visual analytics methodology for eye movement studies. *IEEE Trans. Visual. Comput. Graph.* **18**(12), 2889–2898 (2012)
2. Blascheck, T., Burch, M., Raschke, M., Weiskopf, D.: Challenges and perspectives in big eye-movement data visual analytics. In: *Proceedings of the 1st International Symposium on Big Data Visual Analytics*. IEEE, Piscataway (2015)
3. Blascheck, T., John, M., Kurzhals, K., Koch, S., Ertl, T.: VA²: a visual analytics approach for evaluating visual analytics applications. *IEEE Trans. Visual. Comput. Graph.* **22**(01), 61–70 (2016)
4. Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D., Ertl, T.: State-of-the-art of visualization for eye tracking data. In: *EuroVis– STARs*, pp. 63–82. The Eurographics Association (2014)
5. Blascheck, T., Kurzhals, K., Raschke, M., Strohmaier, S., Weiskopf, D., Ertl, T.: AOI hierarchies for visual exploration of fixation sequences. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*. ACM, New York (2016)
6. Blascheck, T., Raschke, M., Ertl, T.: Circular heat map transition diagram. In: *Proceedings of the 2013 Conference on Eye Tracking South Africa*, pp. 58–61. ACM, New York (2013)
7. Bojko, A.: Informative or misleading? Heatmaps deconstructed. In: Jacko, J. (ed.) *Human-Computer Interaction. New Trends, LNCS’09*, pp. 30–39. Springer, Berlin (2009)
8. Burch, M., Andrienko, G.L., Andrienko, N.V., Höferlin, M., Raschke, M., Weiskopf, D.: Visual task solution strategies in tree diagrams. In: *Proceedings of the IEEE Pacific Visualization Symposium*, pp. 169–176. IEEE, Piscataway (2013)
9. Burch, M., Kull, A., Weiskopf, D.: AOI Rivers for visualizing dynamic eye gaze frequencies. *Comput. Graph. Forum* **32**(3), 281–290 (2013)
10. Bylinskii, Z., Borkin, M.A., Kim, N.W., Pfister, H., Oliva, A.: Eye fixation metrics for large scale evaluation and comparison of information visualizations. In: Burch, M., Chuang, L., Fisher, B., Schmidt, A., Weiskopf, D. (eds.) *Eye Tracking and Visualization. Foundations, Techniques, and Applications (ETVIS 2015)*, pp. 235–255. Springer, Heidelberg (2016)
11. Chi, E.H.: A taxonomy of visualization techniques using the data state reference model. In: *IEEE Symposium on Information Visualization*, pp. 69–75. IEEE Computer Society, Los Alamitos (2000)
12. Crowe, E.C., Narayanan, N.H.: Comparing interfaces based on what users watch and do. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 29–36. ACM, New York (2000)

13. De Urabain, I.R.S., Johnson, M.H., Smith, T.J.: GraFIX: a semiautomatic approach for parsing low-and high-quality eye-tracking data. *Behav. Res. Methods* **47**(1), 53–72 (2015)
14. Demiralp, C., Cirimele, J., Heer, J., Card, S.: The VERP Explorer: a tool for exploring eye movements of visual-cognitive tasks using recurrence plots. In: Burch, M., Chuang, L., Fisher, B., Schmidt, A., Weiskopf, D. (eds.) *Eye Tracking and Visualization. Foundations, Techniques, and Applications (ETVIS 2015)*, pp. 41–55. Springer, Heidelberg (2016)
15. Duchowski, A.: *Eye Tracking Methodology: Theory and Practice*, 2nd edn. Science+Business Media. Springer, New York (2007)
16. Duchowski, A.T., Driver, J., Jolaoso, S., Tan, W., Ramey, B.N., Robbins, A.: Scan path comparison revisited. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 219–226. ACM, New York (2010)
17. Fayyad, U., Piatetsky-Shapiro, G., Smyth, P.: The KDD process for extracting useful knowledge from volumes of data. *Commun. ACM* **39**(11), 27–34 (1996)
18. Goldberg, J.H., Helfman, J.I.: Scanpath clustering and aggregation. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 227–234. ACM, New York (2010)
19. Goldberg, J.H., Helfman, J.I.: Visual scanpath representation. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 203–210. ACM, New York (2010)
20. Grindinger, T., Duchowski, A., Sawyer, M.: Group-wise similarity and classification of aggregate scanpaths. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 101–104. ACM, New York (2010)
21. Haber, R.B., McNabb, D.A.: Visualization idioms: a conceptual model for visualization systems. In: Nielson, G.M., Shriver, B.D., Rosenblum, L.J. (eds.) *Visualization in Scientific Computing*, pp. 74–93. IEEE Computer Society Press, Los Alamitos (1990)
22. Heinrich, J., Weiskopf, D.: State of the art of parallel coordinates. In: *STAR Proceedings of Eurographics*, pp. 95–116. The Eurographics Association (2013)
23. Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., Van de Weijer, J.: *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford University Press, Oxford (2011)
24. Inselberg, A.: *Parallel Coordinates: Visual Multidimensional Geometry and Its Applications*. Springer, New York (2009)
25. Just, M.A., Carpenter, P.A.: Eye fixations and cognitive processes. *Cognit. Psychol.* **8**, 441–480 (1976)
26. Kim, S.H., Dong, Z., Xian, H., Upatasing, B., Yi, J.S.: Does an eye tracker tell the truth about visualizations? Findings while investigating visualizations for decision making. *IEEE Trans. Visual. Comput. Graph.* **18**(12), 2421–2430 (2012)
27. Kirchner, H., Thorpe, S.J.: Ultra-rapid object detection with saccadic eye movements: visual processing speed revisited. *Vis. Res.* **46**(11), 1762–1776 (2006)
28. Kurzhals, K., Bopp, C.F., Bässler, J., Ebinger, F., Weiskopf, D.: Benchmark data for evaluating visualization and analysis techniques for eye tracking for video stimuli. In: *Proceedings of the Workshop Beyond Time and Errors: Novel Evaluation Methods for Visualization*, pp. 54–60. ACM, New York (2014)
29. Kurzhals, K., Fisher, B.D., Burch, M., Weiskopf, D.: Evaluating visual analytics with eye tracking. In: *Proceedings of the Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization*, pp. 61–69. ACM, New York (2014)
30. Kurzhals, K., Heimerl, F., Weiskopf, D.: ISeeCube: visual analysis of gaze data for video. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 43–50. ACM, New York (2014)
31. Kurzhals, K., Hlawatsch, M., Heimerl, F., Burch, M., Ertl, T., Weiskopf, D.: Gaze stripes: image-based visualization of eye tracking data. *IEEE Trans. Visual. Comput. Graph.* **22**(1), 1005–1014 (2016)
32. Kurzhals, K., Weiskopf, D.: Space-time visual analytics of eye-tracking data for dynamic stimuli. *IEEE Trans. Visual. Comput. Graph.* **19**(12), 2129–2138 (2013)
33. Kurzhals, K., Weiskopf, D.: AOI transition trees. In: *Proceedings of the Graphics Interface Conference*, pp. 41–48. Canadian Information Processing Society (2015)

34. Li, X., Çöltekin, A., Kraak, M.J.: Visual exploration of eye movement data using the space-time-cube. In: Fabrikant, S., Reichenbacher, T., Kreveld, M., Christoph, S. (eds.) *Geographic Information Science, LNCS'10*, pp. 295–309. Springer, Berlin (2010)
35. Nguyen, T.H.D., Richards, M., Isaacowitz, D.M.: Interactive visualization for understanding of attention patterns. In: Burch, M., Chuang, L., Fisher, B., Schmidt, A., Weiskopf, D. (eds.) *Eye Tracking and Visualization. Foundations, Techniques, and Applications (ETVIS 2015)*, pp. 23–39. Springer, Heidelberg (2016)
36. Pirolli, P., Card, S.: The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In: *Proceedings of the International Conference on Intelligence Analysis*, vol. 5, pp. 2–4 (2005)
37. Rähkä, K.J., Aula, A., Majaranta, P., Rantala, H., Koivunen, K.: Static visualization of temporal eye-tracking data. In: Costabile, M.F., Paternò, F. (eds.) *Human-Computer Interaction-INTERACT 2005, LNCS'05*, vol. 3585, pp. 946–949. Springer, Berlin/New York (2005)
38. Raschke, M., Herr, D., Blascheck, T., Burch, M., Schrauf, M., Willmann, S., Ertl, T.: A visual approach for scan path comparison. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 135–142. ACM, New York (2014)
39. Richardson, D.C., Dale, R.: Looking to understand: the coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cognit. Sci.* **29**(6), 1045–1060 (2005)
40. Rodrigues, R., Veloso, A., Mealha, O.: A television news graphical layout analysis method using eye tracking. In: *Proceedings of the International Conference on Information Visualization (IV)*, pp. 357–362. IEEE Computer Society, Los Alamitos (2012)
41. Salvucci, D.D., Goldberg, J.H.: Identifying fixations and saccades in eye-tracking protocols. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 71–78. ACM, New York (2000)
42. Schulz, C., Burch, M., Beck, F., Weiskopf, D.: Visual data cleansing of low-level eye-tracking data. In: Burch, M., Chuang, L., Fisher, B., Schmidt, A., Weiskopf, D. (eds.) *Eye Tracking and Visualization. Foundations, Techniques, and Applications (ETVIS 2015)*, pp. 199–216. Springer, Heidelberg (2016)
43. Smith, T.J., Mital, P.K.: Attentional synchrony and the influence of viewing task on gaze behavior in static and dynamic scenes. *J. Vis.* **13**(8), 16:1–16:24 (2013)
44. Stellmach, S., Nacke, L., Dachsel, R.: Advanced gaze visualizations for three-dimensional virtual environments. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 109–112. ACM, New York (2010)
45. Tsang, H.Y., Tory, M.K., Swindells, C.: eSeeTrack – visualizing sequential fixation patterns. *IEEE Trans. Visual. Comput. Graph.* **16**(6), 953–962 (2010)
46. Tversky, B., Morrison, J.B., Bétrancourt, M.: Animation: can it facilitate? *Int. J. Hum. Comput. Stud.* **57**(4), 247–262 (2002)
47. Weibel, N., Fouse, A., Emmenegger, C., Kimmich, S., Hutchins, E.: Let's look at the cockpit: exploring mobile eye-tracking for observational research on the flight deck. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 107–114. ACM, New York (2012)
48. West, J.M., Haake, A.R., Rozanski, E.P., Karn, K.S.: eyePatterns: software for identifying patterns and similarities across fixation sequences. In: *Proceedings of the Symposium on Eye Tracking Research & Applications*, pp. 149–154. ACM, New York (2006)
49. Yarbus, A.L.: *Eye Movements and Vision*. Plenum Press, New York (1967)

Eye Tracking and Visualization

Foundations, Techniques, and Applications. ETVIS 2015

Burch, M.; Chuang, L.; Fisher, B.; Schmidt, A.; Weiskopf,
D. (Eds.)

2017, XII, 258 p. 123 illus., 105 illus. in color.,

Hardcover

ISBN: 978-3-319-47023-8