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# State-of-the-Art of Visualization for Eye Tracking Data

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**Abstract**

*Eye tracking technology is becoming easier and cheaper to use, resulting in its increasing application to numerous fields of research. The data collected during an eye tracking experiment can be analyzed by statistical methods and/or with visualization techniques. Visualizations can reveal characteristics of fixations, saccades, and scanpath structures. In this survey, we present an overview of visualization techniques for eye tracking data and describe their functionality. We classify the visualization techniques using nine categories. The categories are based on properties of eye tracking data, including aspects of the stimuli and the viewer, and on properties of the visualization techniques. The classification of about 90 publications including technical as well as application papers with modifications of common visualization techniques are described in more detail. We finally present possible directions for further research in the field of eye tracking data visualization.*

Categories and Subject Descriptors (according to ACM CCS): [General and reference]: Document types—Surveys and overviews [Human-centered computing]: Visualization—Visualization techniques [Human-centered computing]: Visualization—Visualization design and evaluation methods

## 1. Introduction

Eye tracking has become a widely used method to analyze user behavior in marketing, neuroscience, human-computer interaction, and visualization research [Duc02, TCSC13]. Apart from measuring completion times and recording accuracy rates of correctly given answers during the performance of visual tasks in classical controlled user experiments, eye tracking-based evaluations provide additional information on how visual attention is distributed and changing for a presented stimulus. Eye tracking devices record gaze points of a participant as raw data. Afterwards, these gaze points can be aggregated into fixations and saccades for measuring which areas on the stimulus have been focused on. If necessary, areas of interest (AOIs) can be defined to concentrate the analysis on specific regions on the stimulus.

Due to the wide field of applications of eye tracking and various kinds of research questions, different approaches have been developed to analyze eye tracking data such as statistical algorithms (either descriptive or inferential) [HNA*11], string editing algorithms [PS00, DDJ*10], visualization-related techniques, and visual analytics techniques [AABW12]. Regardless of whether statistical or visual methods are used for eye tracking data analysis, a large amount of data generated during eye tracking experiments has to be handled. For example, a user experiment with 30 participants, three types of tasks, and 30 stimuli for each task leads to 2,700 scanpaths in total. Each scanpath typically consists of a large number of fixations and every fixation aggregates gaze points. The number of these gaze points depends on the recording rate of eye tracking devices. In this example, more than 10,000 fixations and more than 100,000 gaze points have to be stored, formatted, and analyzed to finally confirm or reject one or more hypotheses. Besides analyzing eye tracking data with respect to quantitative metrics such as fixation count, distribution, and position, saccadic amplitude, and pupil size, semantic information about which areas on the stimulus were focused on gives additional information to understand viewing strategies of participants.

Where statistical analysis mainly provides quantitative results, visualization techniques allow researchers to analyze different levels and aspects of the recorded eye tracking data in an explorative and qualitative way. Visualization techniques help analyze the spatio-temporal aspect of eye tracking data and the complex relationships within the data. This more qualitative exploration aims at finding hypotheses that can be investigated with statistical methods later on. Due to the increasing complexity of tasks and stimuli in eye tracking experiments, we believe that visualization will play

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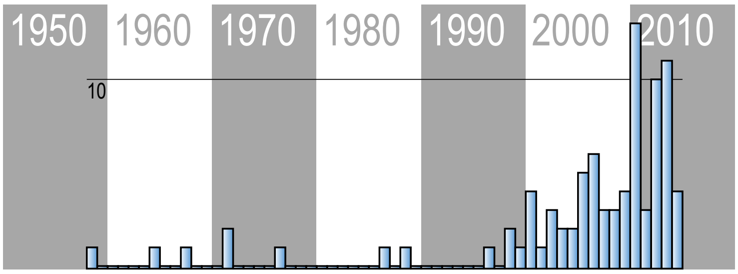


**Figure 1:** *Histogram of all publications of this survey, relevant for eye tracking data visualization techniques. The number of published articles, conference papers, and books has strongly increased during the last decade.*

an increasingly important role in future eye tracking analysis. Thus, the contribution of the survey is manifold: First, based on a taxonomy for eye tracking terms, a classification system for stimuli and visualization techniques is formulated. Second, we assign papers from the literature to those classes. Third, based on these results, we identify questions for future development of eye tracking visualization techniques.

Evaluation has become an important step in the development of new visualization techniques. Eye tracking is one means of evaluating those newly developed approaches. Thus, analyzing eye tracking data with visualization techniques is just a logical step that followed. The number of published articles, conference papers, and books about eye tracking visualizations has strongly increased during the last decade. Figure 1 shows a histogram of all relevant publications with visualization techniques for eye tracking data, that are included in this survey. Especially, after the first IEEE Symposium on Information Visualization in 1995 [GE95], the number of visualization techniques for eye tracking has steadily increased. However, so far a comprehensive survey of visualization techniques for eye tracking, structuring and discussing the approaches is still missing. Since eye tracking is used in a wide application range and new challenges arise, such as eye tracking in the 3D environment, an exhaustive survey is necessary to find missing visualization techniques.

Due to the wide application range of eye tracking, the development of visualization techniques has become an interdisciplinary challenge that requires a comprehensive literature research over many different disciplines. To satisfy this requirement, we reviewed the main visualization and visual analytics conferences (VIS, EuroVIS, EuroVA), the ACM Digital Library, and the IEEE Xplorer Digital Library, but also the top conference on eye tracking research (ETRA), and main journals of usability research (Journal of Human Factors), psychology (Behavior Research Methods), and cognitive sciences (Cognitive Science Journal). This literature research resulted in about 90 papers found on eye tracking data visualization. To allow the reader to better find adequate visualization techniques for his or her analysis, we subdivided the visualization techniques into three main classes: point-based visualization techniques, AOI-based visualization techniques, and visualization techniques using both. Next, we tagged the visualization techniques with information about stimulus type, in-context visualizations, animated visualizations, interactive visualizations, and active stimulus content. A detailed description of this classification will be given in the next section. The main part of the paper is the presentation of the different visualization techniques with respect to this classification system. At the end, we will discuss possibilities for future research.

## 2. Taxonomy

Before we present our taxonomy classifying visualization techniques, we first define the basic terminology related to eye tracking data (Section 2.1). The taxonomy is subdivided into two categories: those related to stimuli of eye tracking experiments (Section 2.2) and those related to visualization techniques (Section 2.3). Other taxonomy papers target areas different from ours, e.g., taxonomies restricted to the stimulus alone [SNDC09], the dimensionality of the visualization [Špa08], or the eye tracking data [RTSB04]. Our taxonomy includes more categories to obtain a fine-grained categorization of the visualization techniques and to find out what visualization techniques might be missing.

### 2.1. Terminology

Eye tracking devices record gaze points performed by a participant on a stimulus. The recording rates depend on the characteristics of the devices. State-of-the-art devices allow rates between 60 and 120 Hz. Some newer high speed eye trackers support recording rates of 240 Hz or more. The recording rate specifies how many gaze points are recorded per second. However, eye tracking research is not using raw gaze points. Rather, different data types which are shown in Figure 2 can be distinguished and will be defined in the following in more detail. For each data type different metrics are used in an eye tracking analysis. The most important metrics for each data type will be explained shortly. A comprehensive collection of eye tracking metrics can be found in the book by Holmqvist et al. [HNA*11].

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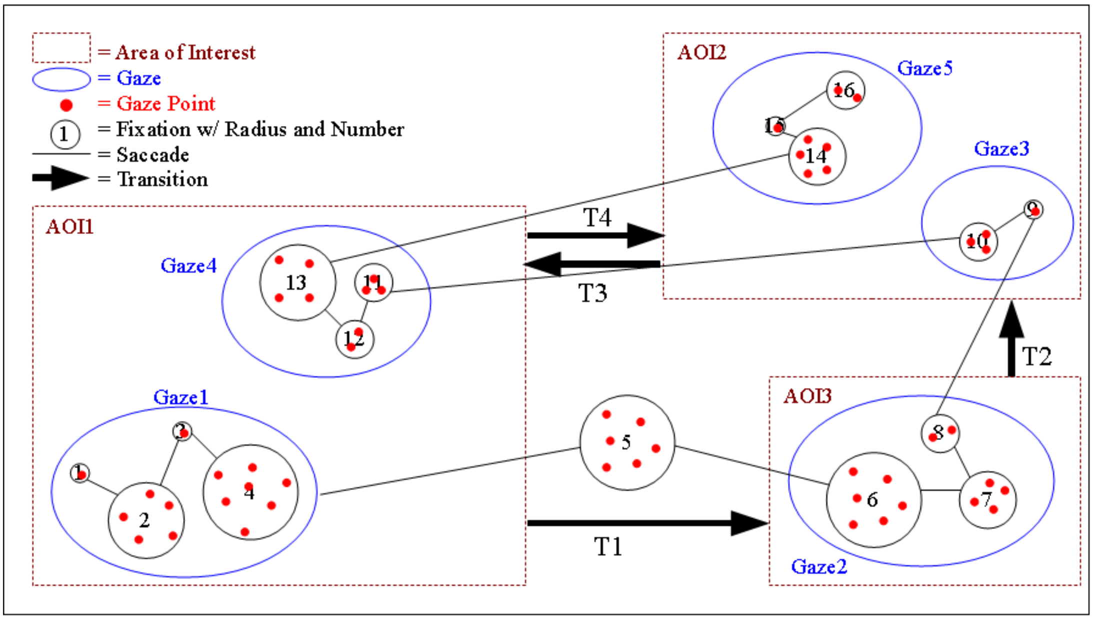


**Figure 2:** *Gaze points are spatially and temporally aggregated into fixations. Fixations are connected by saccades and have a certain duration represented by the radius. A temporal order of fixations is a gaze, however, only if the fixations are within an AOI. An AOI is a region of specific interest on the stimulus. A saccade from one AOI to the next is called a transition. A complete sequence of fixations and saccades is called a scanpath.*

**Fixation.** A fixation is an aggregation of gaze points. Gaze points are aggregated based on a specified area and timespan. The aggregation area is usually about 20 to 50 pixels, the timespan between 200 and 300 ms [HNA*11]. Common metrics for fixations are the fixation count (i.e. number of fixations), the fixation duration in milliseconds, and the fixation position given as x- and y-coordinates in pixel.

**Saccade.** Saccades describe a rapid eye movement from one fixation to another. They typically last about 30 to 80 ms and are the fastest movement the human body can perform. During this timespan visual information is suppressed [HNA*11]. Typical metrics are the Saccadic amplitude (i.e. the distance the saccade traveled), the saccadic duration in milliseconds, and the saccadic velocity in degrees per second.

**Smooth Pursuit.** During the presentation of dynamic stimuli smooth pursuits can occur. They occur unintentional and only if viewers follow a movement in a presented stimulus. The velocity of the eye during smooth pursuits is about 10 to 30 degrees per second [HNA*11].

**Scanpath.** A sequence of alternating fixations and saccades is called a scanpath. A scanpath can give information about the search behavior of a participant. An ideal scanpath would be a straight line to a specified target [CHC10]. Deviance from this ideal scanpath can be interpreted as poor search [GK99]. Scanpath metrics include the convex hull (i.e. which area is covered by the scanpath), scanpath length in pixels, or scanpath duration in milliseconds.

**Stimulus.** A stimulus can be any visual content presented to participants during an eye tracking experiment. Typically, static and dynamic stimuli, with either active or passive content are differentiated. Usually, 2D stimuli are presented to participants. However, in recent years, 3D stimuli have become a focus of research as well.

**Area of Interest.** Areas of interest (AOIs) or regions of interest (ROIs) are parts of a stimulus that are of high importance for a hypothesis. In 3D stimuli, AOIs can also be models or objects of interest (OOIs). For dynamic stimuli, dynamic AOIs have to be defined. AOIs can either be created beforehand or after an eye tracking experiment. Usually, AOIs are created based on the semantic information of the stimulus. A transition is a movement from one AOI to another. Typical metrics for AOIs are the transition count (i.e. number of transitions between two AOIs), the dwell time within an AOI in milliseconds, and the AOI hit which defines if a fixation is within an AOI or not.

## 2.2. Stimulus-Related Categories

The first part of the taxonomy is based on a categorization of stimuli. The type of stimulus can have a great influence on the choice and design of a visualization technique. The

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first categorization divides stimuli into point-based and AOI-based data. Furthermore, stimuli can be distinguished as being static or dynamic, with active or passive content, and representing 2D or 3D content. The viewing task would be another type for classification, however it will not be included in our taxonomy.

**Point-based versus AOI-based.** Eye tracking data of a stimulus can be evaluated in a point-based or AOI-based fashion [AABW12]. Point-based evaluation of eye tracking data focuses on the overall movement and its spatial or temporal distribution. Here, a semantic annotation of data is not required. Depending on the stimulus, a point-based evaluation is not always sufficient for specific analysis tasks (e.g., comparison of asynchronous eye tracking data). Therefore, an annotation of identified AOIs on the stimulus can be used for applying AOI-based metrics. In AOI-based metrics the transition and relation of AOIs is of interest. This classification will be used as the first level to distinguish between different visualization techniques.

**Static versus Dynamic Stimuli.** Static stimuli can, for example, be static visualizations, pictures, or advertisements where the stimulus does not change. Dynamic stimuli can be videos, dynamic visualizations, or real-world scenarios. Some visualization techniques are presented as an overlay on the stimulus and can be used with static and dynamic stimuli. Other visualization techniques depend on a static stimulus and cannot be applied to dynamically changing content.

**Passive versus Active Stimulus Content.** The viewer's mode of interaction is an important factor for data visualization and how the graphical user interface for a visualization technique is designed. Viewers can watch presented stimuli passively without interfering actions. The stimulus can be either static or dynamic, i.e., the presentation of pictures or videos. A synchronization between recordings of different viewers is possible with minor effort, allowing one to compare multiple viewers and search for similarities or differences in their scanpaths. Viewers can also actively influence the stimulus by their actions, here the stimulus becomes dynamic. Eye tracking of interactive applications are good examples of individual recordings that result from the active integration of the viewer into the experiment. Comparing these individually recorded data sets is a non-trivial task, since a synchronization of the data is difficult [Duc07].

**2D versus 3D Stimuli.** 2D stimuli have been mostly investigated and can, for example, be static or dynamic 2D visualizations, videos, or web pages. Stimuli representing 3D models or objects are being investigated more in recent years. Here, 3D stimuli can either be represented as stereoscopic images on 3D screens, or using head-mounted eye trackers in real or virtual world scenarios. A challenge with 3D stimuli is mapping the fixations onto the correct geometrical model of the stimulus.

**Viewing Task.** Although a given task during an eye tracking experiment has a significant influence on the eye movement of viewers [AHR98], we decided not to use the task as a categorization factor, since many visualization techniques do not depend explicitly on the given task for a successful interpretation of the data.

### 2.3. Visualization-Related Categories

There are numerous taxonomies for visualizations based on different aspects. Some taxonomies focus on the data dimension or type [Chi00, TM04], on interaction techniques [YaKSJ07, Shn96], on the visualization task [BM13], or on specific visualization types [LPP*06, CM97]. However, for eye tracking visualizations those taxonomies are either too general or too concrete. Our taxonomy uses a categorization based on the eye tracking data types and the number of users represented. We distinguish between animated and static, 2D and 3D, in-context and not in-context, as well as interactive and non-interactive visualizations. Lastly, we want to introduce the field of visual analytics as one means to evaluate eye tracking data.

**Statistical Graphics.** The most commonly used visualization techniques for eye tracking data are statistical diagrams such as line charts, bar charts, box plots, or scatter plots. These visualization techniques can be used for analyzing eye tracking data quantitatively. This survey will mostly focus on approaches for qualitative or explorative data analysis. Statistical graphics used for eye tracking data are only briefly discussed in Section 3.

**Temporal, Spatial, and Spatio-Temporal Visualizations.** The visualization techniques in this survey will be classified as either temporal, spatial, or spatio-temporal. The temporal dimension focuses on time and is usually visualized with a timeline as one axis. The spatial dimension of the data focuses on the x-, y-, and if relevant, the z-coordinates of fixations. For AOI-based visualization techniques, the spatial domain contains the AOIs and their relation to each other. The third data type is the combination of both, called spatio-temporal. Here, temporal as well as spatial aspects of the data are included into the visualization approach.

**Static Versus Animated Visualizations.** Static visualizations usually use a time-to-space mapping of the data. For dynamic stimuli creating a static visualization often requires predefined AOI definitions, since the spatial linking to the dynamically changing content is commonly hard to achieve. Animated visualizations use a time-to-time mapping of the data by sequentially presenting certain points in time from the data. This allows in-context visualizations with an overlay of the visualization over the stimulus, keeping the stimulus data and the visualization in the same domain. However, this requires quite complex layout algorithms that follow aesthetic drawing criteria [Pur97] for each static

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image in the sequence. Additionally, aesthetic criteria for animation [BBD09] have to be applied to preserve a viewer's mental map.

**Single User Versus Multiple Users.** An important factor for eye tracking analysis is the number of users represented in a visualization technique. Representing single users allows the analyst to inspect the viewing behavior of one participant. However, visualizing multiple users at the same time can allow one to find strategies of groups, but these representations might suffer from visual clutter if too much data is represented at the same time. Here, optimization strategies, such as averaging or bundling of lines might be used, to achieve better results [HFG06, HEF*13].

**2D Versus 3D Visualizations.** 2D visualizations represent only two different data types at the same time, for example, one spatial dimension and the temporal, or both spatial dimensions. Usually, eye tracking data from 2D stimuli is represented with 2D visualizations. Representing 2D stimuli using 3D visualizations can be helpful as in the case of space-time cubes. Here, the spatial as well as the temporal data is visualized. However, the third dimension has to be handled with care because of perceptual issues related to 3D visualizations. Visualizing 3D data in a 2D domain removes one dimension and leads to data loss. However, this can make the analysis easier. To avoid data loss and represent all data domains, 3D visualization techniques are developed for 3D eye tracking data.

**In-Context Versus Not In-Context Visualizations.** In-context visualizations link stimulus and visualization with each other, such as overlays over the stimulus or AOIs with thumbnail images. This allows a mental map preservation as the stimulus is shown in the background. Visualization methods that do not include the stimulus in the visualization are not in-context visualizations. This is often the case for AOI-based visualization techniques. Not in-context visualizations have the problem that the topology of the AOIs and the mental map is lost. However, if the relation between AOIs is more important loosing the topological information is an acceptable trade off.

**Interactive Versus Non-Interactive Visualizations.** Non-interactive visualizations usually represent the data with a fixed set of parameters. The user has no option to influence those parameters either because there are no options or because they have been predefined. In contrast, interactive visualizations allow the user to explore the data beyond what is represented at the beginning. For example, the user can navigate through time, zoom and filter the represented data, or obtain detailed information about the data.

**Visual Analytics.** When visualization techniques alone are not able to handle the vast amount of generated eye tracking data, the emerging discipline of visual analytics can be a convenient option for explorative data analysis. Algorithmic concepts such as data mining or knowledge discovery in databases combined with visualization techniques and the perceptual abilities of the human viewer can be a good means to uncover common structures or strategies among the study participants. In the eye tracking domain, different visual analytics systems have been developed over the last years. One example of how existing visual analytics systems can be used with eye tracking data is described by Andrienko et al. [AABW12]. The authors investigated how visual analytics approaches for geographic information science (GIScience) can be adapted for analyzing spatio-temporal data.

### 2.4. Classification Structure

Based on the above categories, we divide the papers of eye tracking visualizations into two main subsets that differentiate whether the visualization technique is for point-based or AOI-based analysis. On a second level, we will further segment the visualization techniques based on temporal, spatial, and spatio-temporal aspects of visualization. Table 1 gives an overview of all eye tracking visualizations that introduced a new visualization technique, an improvement of an existing visualization technique, or that adapted an existing visualization technique for its application to eye tracking data. The table also classifies the visualization techniques based on the above mentioned two levels. The upper part contains the point-based visualization techniques that will be described in Section 4 and the lower part of the table shows the visualization-related visualization techniques described in Section 5. The middle part of the table contains papers from authors which present approaches where one is point-based and another AOI-based. Each approach is then described in the corresponding section. The individual sections on point-based and AOI-based visualization techniques are further subdivided into temporal, spatial, and spatio-temporal visualization techniques. This is also represented by the first column of the table. In the case of point-based visualization techniques, the temporal approaches are namely timeline visualizations, spatial approaches are attention maps, and the spatio-temporal approaches are subdivided into scanpaths and space-time cube visualizations as they represent two different concepts. In the AOI-based section, first timeline as temporal approaches, and then relational visualization techniques as spatial approaches are discussed. The spatio-temporal techniques are mainly concerned with 3D data and are not included due to space limitations. 3D has just recently started to be investigated in eye tracking research, and therefore is not the focus of most of the research so far. Therefore, some of the references mentioned in the table are not described in the text itself. Furthermore, the table displays all remaining categorizing factors described in the taxonomy, starting with visualization categories and then the stimulus categories.

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**Table 1:** *List of all references that introduced a new, an improvement, or an adaption of an existing visualization technique. The references are classified by the visualization-related and stimulus-related categories described in Sections 2.2 and 2.3.*

| | Reference | Visualization | | | | | | | | | | | | | Stimulus | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Temporal | Spatial | Spatio-temporal | Animated | Static | Single user | Multiple users | 2D | 3D | In-context | Not in-context | Interactive | Non-interactive | Static | Dynamic | Active content | Passive content | 2D | 3D |
| Point-based | Grindinger et al. [GDS10] | ● | ○ | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ● | ○ | ● | ● | ○ |
| | Goldberg & Helfman [GH10c] | ● | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Bojko [Boj09] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Velichkovsky & Hansen [VH96] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Wooding [Woo02] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ● | ● | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Latimer [Lat88] | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Kurzhals & Weiskopf [KW13] | ○ | ● | ● | ● | ● | ○ | ● | ● | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ |
| | Paletta et al. [PSF*13b] | ○ | ● | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| | Noton & Stark [NS71b] | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Ramloll et al. [RTSB04] | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● |
| | Mackworth & Mackworth [MM58] | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ |
| | Yarbus [Yar67] | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Lankford [Lan00] | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ● | ● | ○ | ○ | ● | ● | ● | ● | ● | ● | ○ |
| | Burch et al. [BSRW14] | ○ | ○ | ● | ○ | ● | ● | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Hembrooke et al. [HFG06] | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Chen et al. [CAS13] | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Li et al. [LÇK10] | ○ | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ○ |
| | Hurter et al. [HEF*13] | ○ | ○ | ● | ● | ● | ● | ● | ● | ○ | ● | ○ | ○ | ● | ● | ● | ● | ● | ● | ○ |
| | Dorr et al. [DJB10] | ○ | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ |
| | Duchowski et al. [DPMO12] | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ |
| | Duchowski & McCormick [DM98] | ○ | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ |
| Both | Stellmach et al. [SND10b] | ● | ● | ● | ○ | ● | ● | ○ | ● | ● | ● | ● | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| | Weibel et al. [WFE*12] | ● | ○ | ● | ● | ● | ● | ○ | ● | ○ | ● | ● | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| | Pfeiffer [Pfe12] | ○ | ● | ● | ● | ○ | ● | ● | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| AOI-based | Špakov & Räihä [ŠR08] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ● | ○ |
| | Beymer & Russel [BR05] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ● | ○ |
| | Räihä et al. [RAM*05] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Kim et al. [KDX*12] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ |
| | Crowe & Narayanan [CN00] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Holsanova [Hol01] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Itoh et al. [ITS00] | ● | ○ | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ○ | ● |
| | Pellacini et al. [PLG06] | ● | ○ | ○ | ○ | ● | ● | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Kurzhals et al. [KHW14] | ● | ○ | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ |
| | Burch et al. [BKW13] | ● | ○ | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ |
| | Raschke et al. [RCE12] | ● | ○ | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Richardson & Dale [RD05] | ● | ○ | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Tsang et al. [TTS10] | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| | Blascheck et al. [BRE13] | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ |
| | Goldberg & Kotval [GK99] | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ● | ○ | ● | ○ |
| | Egusa et al. [ETK*08] | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Itoh et al. [IHN98] | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ○ | ● |
| | Schulz et al. [SSF*11] | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ○ | ● | ○ | ● | ● | ○ | ○ | ● |
| | West et al. [WHRK06] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ |
| | Goldberg & Helfman [GH10b] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Siirtola et al. [SLHR09] | ○ | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ |
| | Baldauf et al. [BFH10] | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ● | ○ | ○ | ● | ● | ○ | ○ | ● |
| | Duchowski et al. [DMC*02] | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● | ● | ○ | ○ | ● | ○ | ● | ● | ○ | ○ | ● |

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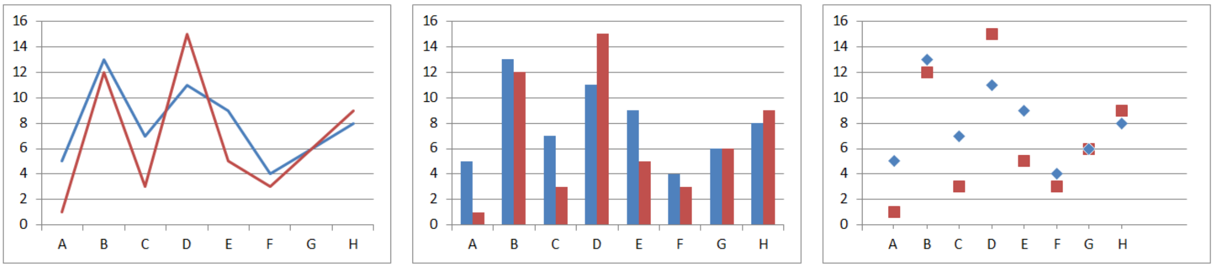


**Figure 3:** *Example of a line chart, bar chart, and scatter plot. Each graph represents the same data set.*

## 3. Statistical Graphics

Before we describe the eye tracking visualization techniques based on our classification, this section summarizes a selection of statistical graphics that are commonly used to visualize eye tracking data, however are not especially developed for it. Figure 3 shows an example of a bar chart, scatter plot, and line chart all representing the same data set.

One of the first papers in eye tracking research uses **line charts** to study eye movement characteristics of children in a TV viewing scenario [GWG*64]. The authors present summarized time durations of different types of eye movements such as mini movements, slides, and saccades in a line chart. Atkins and Zheng [AJTZ12] quantify the difference between doing and watching a manual task. To this end, they present results of recorded fixations in two line charts showing values for x- and y-locations of the fixations. Based on this visualization, the authors then discuss saccadic properties. Smith and Mital [SM13] use line charts to present values of mean fixation durations, mean saccadic amplitudes, and other metrics over time. Additionally, they also use line charts to separately show these metrics for dynamic and static stimuli.

A **bar chart** is mainly employed to display a histogram of an eye tracking metric. Convertino et al. [CCY*03] plot the percentage of the fixation duration for four different combinations of visualization techniques onto a bar chart. Thereby, the authors compare the usability of parallel coordinates with other types of visualizations. To evaluate different methods of image fusion, Dixon et al. [DLN*06] present eye location accuracy with bar charts. A 3D bar chart shows the fixation distribution mainly around the screen center in a TV viewing user experiment by Brasel and Gips [BG08].

**Scatter plots** are commonly used to plot data in a 2D Cartesian diagram. This type of diagram shows relations between two values of a sample. Just and Carpenter [JC76] plot the relation between response latency and angular disparity. Berg et al. [BBM*09] compare human vision and monkey vision. The authors present scatter plots of amplitude and velocity measurements of saccadic movements for both species. Additionally, they compared saliency of humans and monkeys and show results also using a scatter plot.

**Box plots** are a popular visualization technique to present statistical distribution. Hornof and Halverson [HH02] analyze absolute, horizontal, and vertical deviation of fixations for participants of their experiment to monitor the deterioration of the calibration of the eye tracker. Dorr et al. [DMGB10] investigate how similar eye movement patterns of different subjects are when viewing dynamic natural scenes. To compare eye movements they employ normalized scanpath saliency scores and show a boxplot of the computed scores for different movies.

Another type of statistical graphics is the **star plot** used by Goldberg and Helfman [GH10c] to analyze angular properties of scanpaths and by Nakayama and Hayashi [NH10] to study angular properties of fixation positions.

## 4. Point-Based Visualization Techniques

This section comprises all visualization techniques that use spatial and temporal information of recorded data points (i.e., x- and y-coordinates of fixations along with temporal information) for visualization directly. Therefore, a definition of AOIs is not required. These visualization techniques can be used for the analysis of temporal evolution of the position of data points, distribution of attention, scanpath analysis, or spatio-temporal structure of eye tracking data.

### 4.1. Timeline Visualizations

Timelines are a typical approach to visualize temporal data. A point-based timeline visualization represents time on one axis of a coordinate system and eye tracking data on the other axis. Such plots are usually represented in 2D space. Therefore, only one image dimension is left for the fixation data and some reduction from the original x- and y-coordinates has to be performed. For example, fixation position can be split into its x- and y-coordinates and each one can be represented individually as shown in Figures 4 and 5. For the x-coordinate, time is depicted on the y-axis and for the y-coordinate, time is shown on the x-axis [GH10c]. This can be done for static or dynamic stimuli and for one or multiple participants [GDS10]. Such timeline visualizations reduce crossings and overlaps of the saccade lines. Furthermore, the

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visualization technique allows a visual scanpath comparison to measure the similarity of aggregated scanpaths [GDS10]. Additionally, a general overview of scanning tendencies can be seen such as downward and upward scanning, or horizontal shifts [GH10c]. However, the separation into x- and y-coordinates makes it difficult to perceive the combined behavior in the two spatial dimensions.

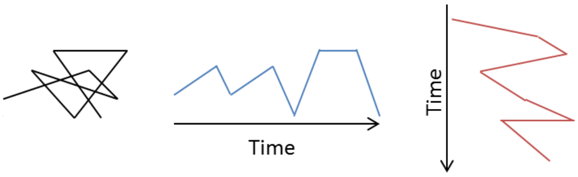


**Figure 4:** *Temporal evolution of a scanpath of one participant separated into x- and y-direction. On the left side a scanpath is shown representing only the saccades. In the middle, the same scanpath is shown representing solely the y-coordinate. Time is represented on the x-axis. On the left side, the scanpath represents the x-coordinate. Time is represented on the y-axis. Figure reprinted with kind permission from Goldberg and Helfman [GH10c].*

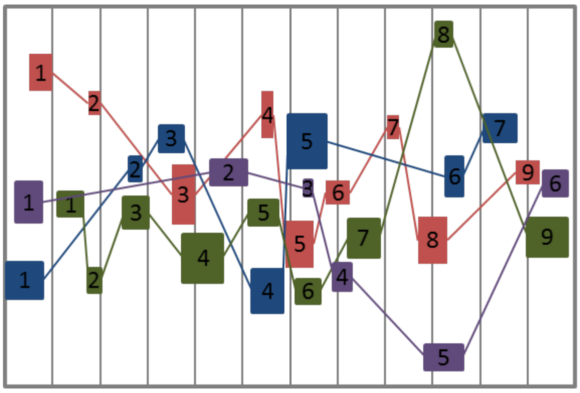

**Figure 5:** *Temporal evolution of scanpaths of multiple participants. Time is represented on the horizontal axis, and the vertical fixation position on the vertical axis. Individual scanpaths are represented by a different color. Figure reprinted with kind permission from Grindinger et al. [GDS10].*

### 4.2. Attention Maps

For spatial visualization techniques, marking fixation positions as an overlay on a stimulus is one of the simplest visualization techniques for recorded eye movements and was applied to dynamic stimuli as early as in 1958 by Mackworth and Mackworth [MM58]. The combined visualization of this fixation data from different participants and the stimulus is denoted *bee swarm* [Tob08]. It is usually presented as an animation to show the temporal changes of fixations.

The aggregation of fixations over time and/or participants is known under the term *attention map*, *fixation map*, or *heat map* and can be found in numerous publications as summarizing illustrations of the analyzed data. The main purpose of attention maps is to obtain an overview of the eye movements and identify regions on the stimulus that attract much attention; the latter is often used to determine AOIs. There are numerous papers describing how to create attention maps (e.g., [ŠM07, Bli10]).

Bojko [Boj09] introduces different types of attention maps depending on the data used, e.g., fixation count attention maps, absolute fixation duration attention maps, relative fixation duration attention maps, or participant percentage attention maps. Each type has its benefits depending on the data needed for an evaluation. In her paper, guidelines for using attention maps are described to avoid misuse and misinterpretation of attention maps. A review of attention maps is given by Holmqvist et al. [HNA*11], who further recommend that attention maps should be used with care.

Classical attention maps are visualized as luminance maps [VH96], 3D landscapes [Lat88, Woo02, HRO11], 2D topographic maps with contour lines [GWP07, DMGB10], or with color coding [Boj09, DPMO12]. To emphasize attended regions, alternative visualization techniques use filter approaches to reduce sharpness and color saturation [DJB10] in the unattended regions.

For dynamic stimuli, like videos, not only the spatial, but also the temporal component of the data is generally visualized by applying dynamically changing attention maps, for example, to identify attentional synchrony of multiple participants [MSHH11]. Attention maps for dynamic stimuli bear the problem that an aggregation of the data cannot be represented statically due to the changing stimulus. This problem is overcome by motion-compensated attention maps using optical flow information between consecutive frames to adjust fixation data based on the moving object that was attended [KW13]. This leads to an attention map where the highest values are on the moving object (cf. Figure 6).

When looking at 3D stimuli, the third dimension has to be included into the attention map. Usually, this is done by representing the attention map on the 3D model itself [Pfe12, PSF*13a, PSF*13b] as shown in Figure 7 on the right. Another possibility is to use a 2D representation of the 3D stimulus and show the attention map on this 2D projections [SND10a] (cf. Figure 7 on the left). However, this leads to data loss due to the reduction of one dimension. A third possibility when multiple objects are shown in a 3D scene is to color code the complete object in the attention map color shown in Figure 7 in the middle [SND10a]. The creation of attention maps for 3D stimuli is often associated with the utilization of additional information about object positions in the stimulus or feature detection.

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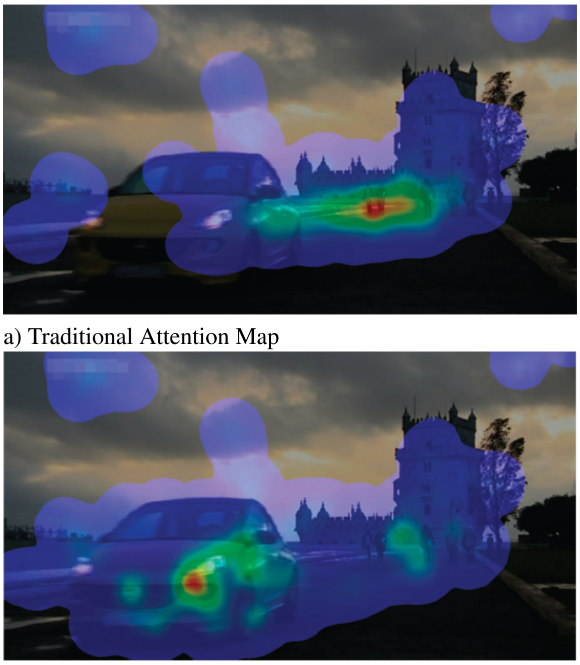
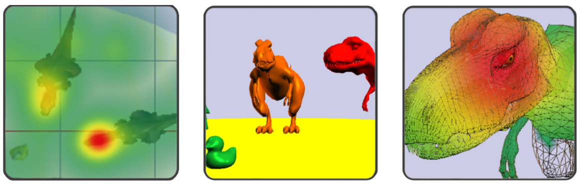


a) Traditional Attention Map

b) Motion-Compensated Attention Map

**Figure 6:** *A conventional attention map for a video scene is displayed in (a), where most of the attention seems to be on two people in the background. The motion-compensated attention map in (b) shows that most attention actually was on the moving car. The motion-compensated attention map uses optical flow information to adjust fixations before the attention map is calculated. Figure reprinted with kind permission from Kurzhals and Weiskopf [KW13] and IEEE.*



a) Projected b) Object-based c) Surface-based

**Figure 7:** *Attention maps for 3D stimuli: (a) the projected attention map, (b) object-based attention map, and (c) surface-based attention map. Figure reprinted with kind permission from Stellmach et al. [SND10b] and ACM.*

### 4.3. Scanpath Visualizations

Spatio-temporal visualization with scanpaths connect consecutive fixations through saccade lines on the stimulus. Noton and Stark [NS71a, NS71b] used the word "scanpath" to describe a fixation path of one subject when viewing a specific pattern. Today, the word "scanpath" describes any sequence of saccades and fixations on a stimulus [HNA*11]. In a typical scanpath visualization, each fixation is indicated by a circle, where the radius corresponds to the fixation duration, see Figure 8. Saccades between fixations are represented by connecting lines [SPK86]. Additional information such as the speed of fixations can be represented by changing the color of the fixation circles [Lan00]. A simple scanpath only shows recorded saccades without printing circles for the fixations [Yar67]. Another interesting eye tracking metric is the convex hull of a scanpath [GK99].

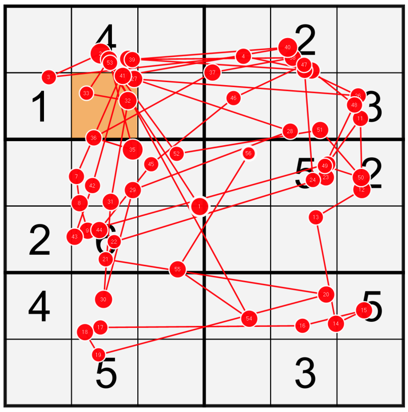


**Figure 8:** *In a typical scanpath visualization, each fixation is indicated by a circle, where the radius corresponds to the fixation duration. Saccades between fixations are represented by connecting lines between these circles.*

Many different approaches exist to show position of fixations and their temporal information in a scanpath layout. However, only scanpath visualizations like the one shown in Figure 8 are broadly used today. It is clear that this kind of visualization quickly produces visual clutter, if several scanpaths are shown in one visualization to study eye movement behavior. On the one hand, if scanpath shapes are different, lines and circles are plotted all across the visualization and it is difficult to find patterns. On the other hand, if scanpath shapes are similar, all saccade lines and fixation circles lie one over the other. Again, it is very difficult to compare these scanpaths with each other.

Many approaches have been presented to overcome the problem of visual clutter. One approach averages or bundles scanpaths [HFG06, HEF*13, CAS13]. A crucial question is to find an adequate averaging or bundling criterion. This question of scanpath similarity has not been fully answered. Another solution is to reduce the ink used in scanpath visualizations and to show a condensed version of a scanpath [GH10c] (cf. Figure 9). The advantage of this visualization technique is that less visual clutter is produced since circles for representing fixations are missing. However, the drawback of this graphical representation is that it is still difficult to visually identify common scanpath patterns by comparing line directions. Another solution is

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to break down the spatial information of fixations into their two dimensions [CPS06]. For example, the vertical and horizontal components of saccades are then shown separately on four sides of an attention map visualization [BSRW14] (cf. Figure 11). The advantage of this visualization technique is that the horizontal and vertical characteristics can be studied independently from each other. However, it demands more mental effort to combine the two separately presented views into one mental image of the scanpath. Still, another possibility is to shown only a part of the scanpath at a time, for example, the proceeding five seconds of a selected timestamp, or time frame [WFE*12].

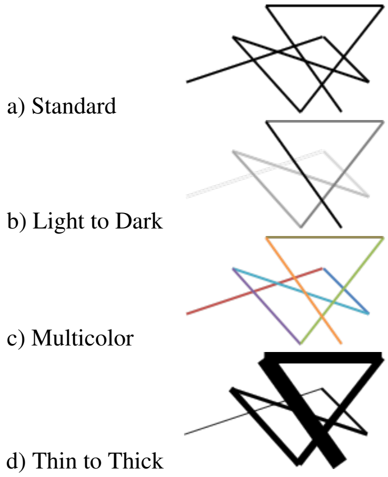


**Figure 9:** *Different types of scaled traces where the scanpath representation is shown without fixation durations. In (a) the normal scaled trace is shown, the line type in (b) is changed from light to dark, in (c) multicolors are used for each saccade. In (d) the line thickness changes from thin to thick. Figure reprinted with kind permission from Goldberg and Helfman [GH10c].*

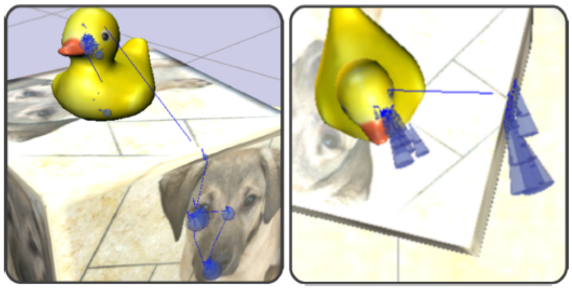

**Figure 10:** *The scanpath in 3D environments is represented with spheres as shown in the left figure. The cones used in the right figure are a different technique to show the scanpath of a participant. This technique allows to encode additional information into the scanpath besides fixation duration. Figure reprinted with kind permission from Stellmach et al. [SND10b] and ACM.*

Another challenge of scanpath visualization is how to show 3D fixation information. Basically, there are two approaches. The first one, shown in Figure 10, is to visualize scanpaths over the original stimulus [DMC*02, SND10b, Pfe12, PSF*13a]. The other one is to warp the stimulus into a 2D representation and to draw scanpath lines on this 2D image [RTSB04]. Besides the question how to adequately show 3D data on a 2D computer screen, which might lead to data loss, visualization of scanpaths from 3D data have same the limitations as their 2D counterparts.

### 4.4. Space-Time Cube

As an alternative spatio-temporal visualization approach, space-time cube (STC) visualizations are commonly used in various research fields [Häg82, Kra03]. For the application to eye tracking data, the 2D spatial domain of the stimulus is extended by a third, temporal dimension. This representation provides an overview of the complete data set and can be applied to static [LÇK10] and dynamic stimuli [DM98, KW13]. With the STC, scanpaths, fixations, and cluster information are visualized statically and allow a direct identification of interesting timespans that would require a sequential search in the data otherwise.

Figure 12 shows an STC for the visualization of fixations and gaze clusters of multiple participants, recorded from a dynamic stimulus. A sliding video plane along the temporal dimension is applied to relate timespans with the dynamic content of the stimulus. Since this 3D visualization bears issues resulting from occlusion, distortion, and inaccurate depth perception, 2D projections of the data can be applied to walls on the sides of the STC.

The main advantage of the STC in comparison to alternative visualization techniques, is the direct overview of data from multiple participants that allows an efficient identification of important AOIs. To this point, an application of the STC to data from multiple participants was applied to synchronizable stimuli only. The application of this visualization technique to asynchronous data (i.e., head-mounted eye tracking data) has not been investigated so far, since it bears additional issues with the spatio-temporal coherence between participants and an AOI-based analysis of this kind of data provides more effective approaches.

## 5. AOI-Based Visualization Techniques

Other than the point-based visualization techniques, AOI-based visualization techniques use additional information of the recorded fixation data that annotates regions or objects on the stimulus that are of special interest to the user. The annotation of AOIs in a static stimulus is often solved by defining bounding shapes around an area or an object. Automatic fixation clustering algorithms are also a common

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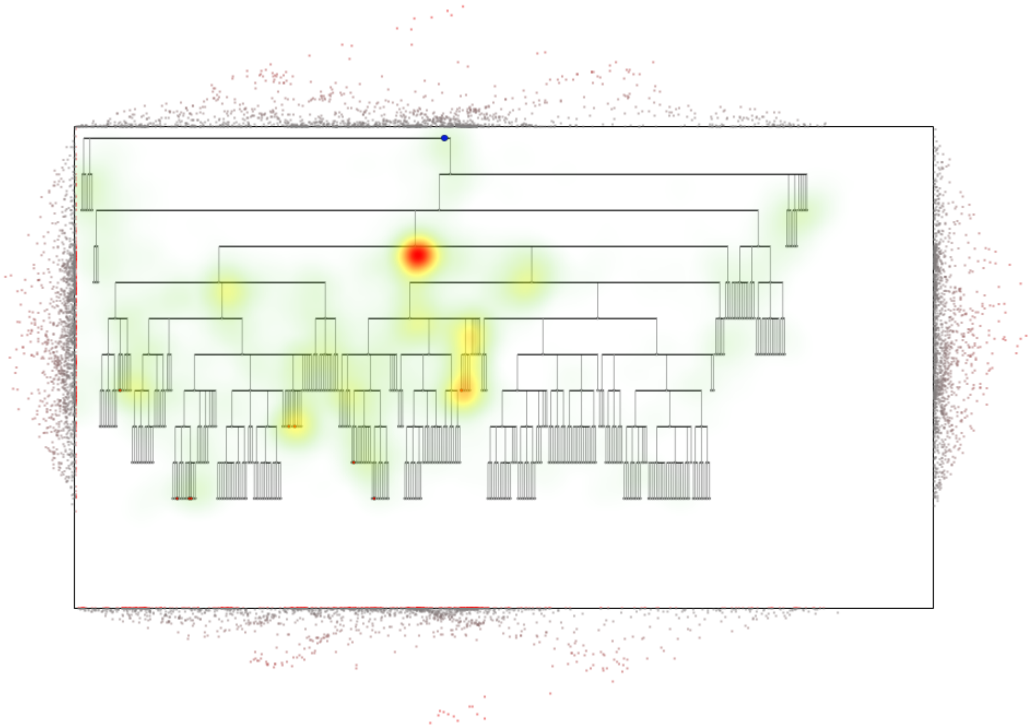

**Figure 11:** *Saccade plots represents the horizontal and vertical position of a saccade on the four sides of a stimulus. The position is represented by a dot and the color coding is used to distinguish between the different saccades. The distance of the dot from the stimulus represents the length of the saccade. If a dot is placed on the left or right side, or top or bottom depends on the position of the saccade in the stimulus. For example, if the saccade is in the top part of the stimulus it is shown on top of the stimulus. Figure based on [BSRW14].*

approach to identify AOIs on a stimulus [PS00, SD04]. With AOI information, various metrics can be applied to the data [PB06, JK03], depending on the user's research questions. A simple in-context approach is an overlay of AOI boundaries on the stimulus with values of the used metric in each AOI (e.g., dwell time in an AOI [RVM12]). The visualization techniques in this section visualize mainly temporal aspects of the data, or relations between AOIs.

### 5.1. Timeline AOI Visualizations

Similar to point-based data, timelines can also be applied to show temporal aspects of AOI-based data. As in the case of point-based timeline visualizations, time is again represented as one axis of a coordinate system. The other axis can represent AOIs or participants.

In the case of AOIs represented on the second axis either one user, averaged information of multiple users, or multiple users separately can be shown. In general, all of these techniques represent the AOIs on separate timelines horizontally or vertically next to each other. A visualization technique representing only one user at a time is shown in Figure 13. Here, either fixations can be represented [RAM*05] or the timespan of an AOI visit can be shown with a rectangle [CN00, Hol01]. The first one is similar to a scanpath as each fixation is represented individually. Therefore, showing multiple participants on top of each other would lead to visual clutter. However, for investigating individual participants, as for example in reading tasks [ŠR08, BR05] where each word represents one AOI, this technique can be helpful as it allows to see backtracks (i.e. backward movements to re-read words). Furthermore, attention maps allow to display fixation frequencies on visual regions of interest over time [Coc09]. There is a condensed version of this visualization technique [KDX*12]. This technique uses only one horizontal axis for time. Each fixation is displayed as a circle on the horizontal axis. The radius of the AOI circle corresponds to the fixation duration and the color of each fixation corresponds to the AOI. This visualization indicates how long and how often an AOI was visited and how many fixations belong to an AOI.

Representing averaged eye tracking data allows to show data of multiple participants in the same visualization without causing visual clutter. This can be represented by a time-

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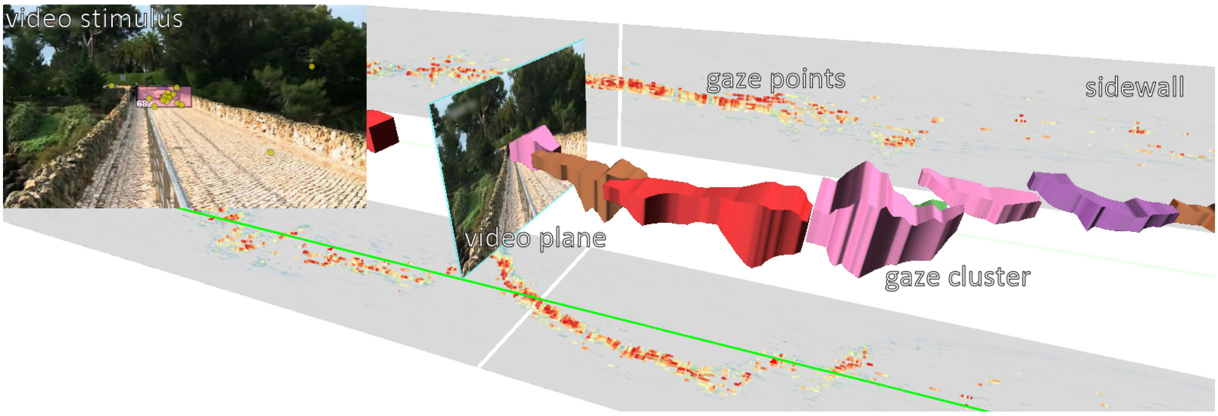


**Figure 12:** *Space-time cube visualization for video eye tracking data. A temporal dimension (green) extends the spatial dimension of the video to a static overview of the data. Gaze clusters are generated automatically from the gaze data of all participants. The gaze points are projected onto the sidewalls of the space-time cube. A frame-by-frame navigation is realized to be able to investigate interesting frames. Figure based on [KW13].*

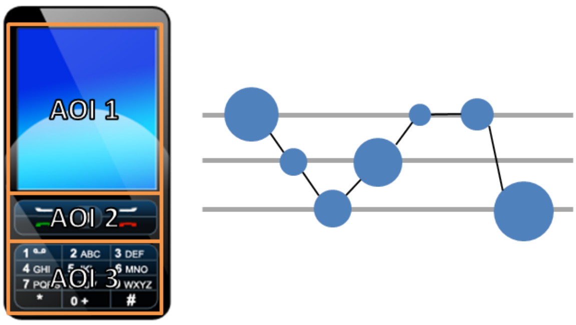


**Figure 13:** *The time plot (on the right) uses a horizontal timeline for each AOI, which are highlighted as rectangles on the stimulus (on the left). Each fixation is drawn as a circle at its point in time and depending on the AOI. The circle radius indicates the fixation duration. Each fixation is connected by a line showing the path. Figure reprinted with kind permission from Räihä et al. [RAM*05].*

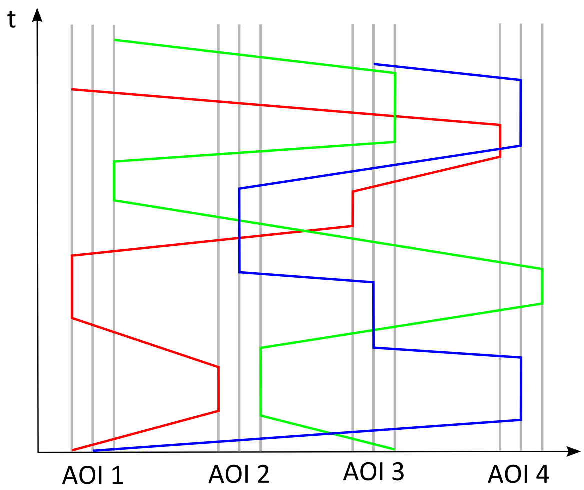


**Figure 14:** *Parallel scanpath visualization maps time onto the y-axis and the AOIs of a stimulus onto the x-axis. For each participant the fixations within an AOI are displayed according to time, and the saccades are represented by lines. Figure based on [RCE12].*

line for each AOI where the AOI visit is indicated by a rectangle [KHW14] or by using AOI rivers [BKW13] shown in Figure 15. Here, the time spent in each AOI and the distribution amongst participants can be seen.

When each participant is represented individually, a timeline for each is shown. Here, a representation with rectangles [HNA*11, WFE*12] or as a scanpath can be used [ITS00, RCE12]. The second visualization, shown in Figure 14, allows a visual scanpath comparison when applying statistical measures [RHB*14].

When participants are used for the second dimension, AOI hits are represented as rectangles on the timeline. This visualization technique is called a scarf plot [RD05]. It can be extended by displaying each fixation with the corresponding duration separately, the color of the fixation indicating the AOI it belongs to [RHOL13]. Participant groups instead of individual participants can be visualized by displaying AOIs with a thumbnail image on the x-axis [TTS10]. This can both be used for static and dynamic stimuli. Condensing the scarf plot even more can be achieved by placing a scarf line for all participants belonging to one group next to each other. A scarf plot technique can also be combined

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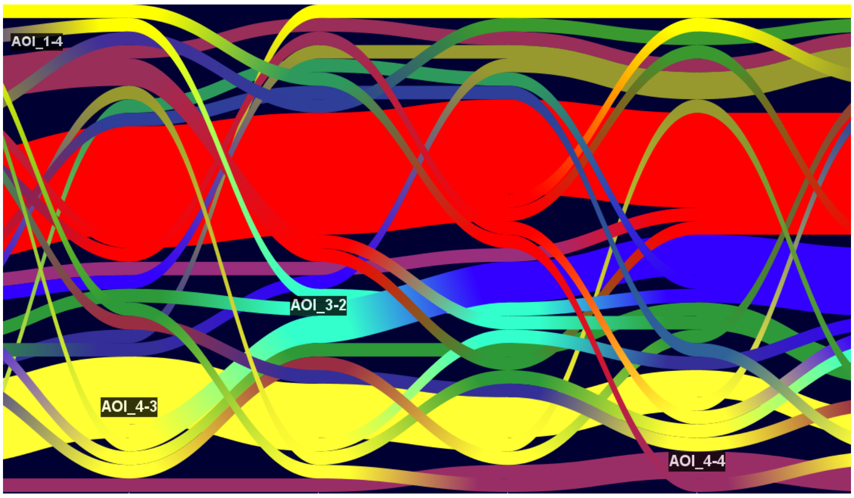


**Figure 15:** *Based on ThemeRiver by Havre et al. [HHWN02], the AOI Rivers display the change of fixation frequencies for each AOI and transitions between AOIs. Time is represented on the x-axis, and each AOI is color-coded individually. Figure based on [BKW13].*

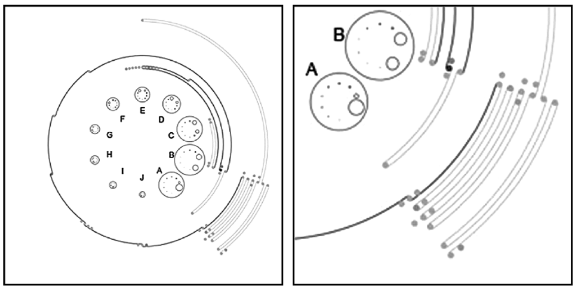

**Figure 16:** *AOIs are placed in a circular layout in the middle of the search path. The size of the AOI circle corresponds to the number of visits to that AOI. The smaller circles inside an AOI represent the transition probability for this AOI from each other AOI. Each fixation is then placed next to its corresponding AOI, which leads to a circular looking search path. Figure reprinted with kind permission from Lorigo et al. [LHB*08].*

with an AOI timeline [KHW14] (cf. Figure 17). For 3D stimuli, the scarf plot can be extended to a the model of interest timeline. It represents objects in a 3D scene instead of AOIs [SND10b]. Each object is assigned a color, and objects belonging to a semantic group can be distinguished by assigning the same color. The times when an object was focused on is displayed on the x-axis with a colored rectangle (cf. Figure 18). The scarf plot can be used to find similar search patterns of participants by calculating the scanpath similarity. Furthermore, it allows to see which AOIs have been looked at the most or the least. However, the transition information between AOIs is lost with these types of visualizations.

A different approach, where the time axis is represented in a circular layout allows to represent AOIs in the middle of the circle (cf. Figure 16). The AOIs can include additional information, as for example, the transition probability [PLG06]. The temporal information of which AOI has been visited at what point in time is represented in this technique. However, it does not scale well if many AOIs are represented at the same time.

### 5.2. Relational AOI Visualizations

Relational visualization techniques use AOIs and show the relationship between them, for example, how often attention changed between two AOIs. Different metrics are represented in the AOI context, for example, the transition percentage or transition probability between two AOIs. A common visualization technique to evaluate transitions between AOIs is the transition matrix [GK99]. A transition matrix orders AOIs horizontally in rows and vertically in columns and each cell contains the number of transitions between two AOIs (cf. Table 2). This matrix representation can be used to evaluate the search behavior of participants. In this case, the stimulus is equally divided up into a grid of AOIs. For example, a densely filled matrix indicates poor search behavior since all AOIs have been focused on for several times. Finding visual search patterns is improved when cells in the transition matrix are colored to show the transition count [LPS*12].

Furthermore, transition matrices can be used to compare multiple participants. The classical transition matrix only

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**Figure 17:** *The upper part shows AOI timelines with attention histograms. The lower part shows scarf plots of ten participants. For each participant a timeline is shown with colored timespans that correspond to the colors of visited AOIs. Black spaces indicate that no AOI was looked at. Figure based on [KHW14].*

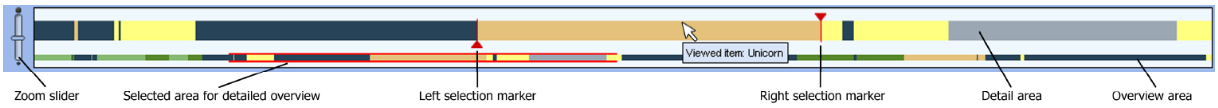


**Figure 18:** *Models of a 3D stimulus are mapped to a timeline depending on the time when and how long they were fixated. Figure reprinted with kind permission from Stellmach et al. [SND10b] and ACM.*

represents one participant. If all participants are represented in the same matrix a visual comparison of search strategies is possible. This is achieved by concatenating the matrices of all participants and assigning a value to each matching sequence between them as shown in Figure 19 [GH10b]. A similar visualization technique using matrices is to place AOIs horizontally as rows and, for example, the task or query of a study vertically as columns. Each cell can then contain different metrics such as fixation duration, or fixation count [ETK*08, SLHR09]. A matrix representation mixes statistical measures with a visual representation. This representation has the advantage of comparing 2D data sets visually. However, if the number of AOIs is high, the matrix becomes large.

The following visualization techniques are not focused on representing statistical information as the transition matrix. Rather, the relation between AOIs is analyzed by using well established visualization techniques such as a directed graph or tree visualization. A directed graph can be used to show transitions between AOIs (cf. Figures 20 and 21). Each node of the graph depicts one AOI and the links depict the transitions. Node size can be varied or color coding can be used to represent different metrics such as fixation count or fixation duration. The thickness of a link can depict the number of transitions between two AOIs as shown in the example in Figure 20. Usually, this type of diagram represents only data of one participant. Averaged values of multiple participants can also be used. Most visualization techniques show the graph independently of the stimulus [IHN98, FJM05, TAK*05, SSF*11, BRE13]. Losing the topological order makes the graph harder to interpret. However, the transition information allows one to see in which order AOIs have been looked at or how often the participant returned to look at an AOI. One example of such a visualization technique is shown in Figure 21. Like the transition matrix, the graph representation does not scale well to a vast amount of AOIs.

**Table 2:** *A classical transition matrix orders AOIs of one participant horizontally in rows and vertically in columns. Each cell represents the number of transitions between two AOIs. The diagonal is empty as no transitions within AOIs can exist [GK99].*

| | AOI 1 | AOI 2 | AOI 3 | AOI 4 |
|---|---|---|---|---|
| AOI 1 | - | 1 | 0 | 3 |
| AOI 2 | 2 | - | 4 | 1 |
| AOI 3 | 0 | 7 | - | 3 |
| AOI 4 | 1 | 0 | 2 | - |

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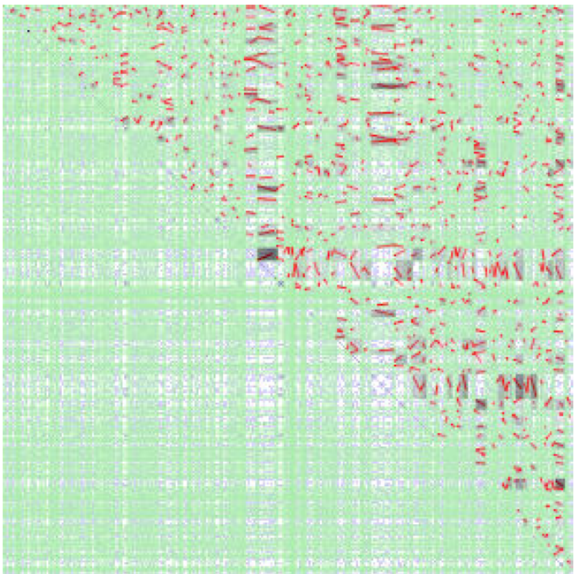

**Figure 19:** *The AOI sequences of multiple users are concatenated and shown in one matrix horizontally and vertically. Each matching sequence is marked by a red line. Green lines show where the AOI sequence of one participant ends. Figure reprinted with kind permission from Goldberg and Helfman [GH10a] and ACM.*

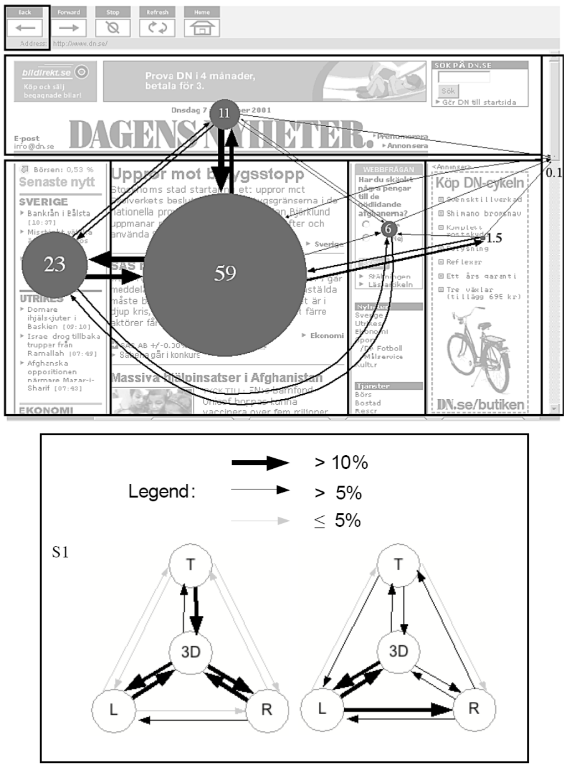


**Figure 20:** *The top figure represents AOIs as circles which are placed on the stimulus. The radius of the circle presents the proportional dwell time. Transitions are depicted by arrows where the thickness presents the number of transitions between two AOIs. Figure reprinted with kind permission from Holmqvist et al. [HHBL03] and Elsevier. The bottom figure depicts AOIs in a triangular layout with the most important AOI in the middle. Transitions are represented by arrows with the thickness corresponding number of transitions. Figure reprinted with kind permission from Tory et al. [TAK*05] and IEEE.*

A tree visualization can be used to compare AOI sequences of participants. A node in the tree represents an AOI. Each branch in the tree represents a different AOI sequence as shown in Figure 22. Thus, many branches represent many different search patterns [WHRK06, TTS10, RHOL13]. This visual comparison of scan patterns allows one to find participant groups. However, it can only be used for short sequences, because for long sequences the difference between participants will be to large and each participant would be a single participant group.

## 6. Discussion of Future Research Directions

Numerous visualization techniques have been developed to visualize different aspects of eye tracking data. Table 1 shows an overview of existing approaches: visualizations for point-based data, AOI-based data, and visualizations for both data types. From this overview, we can recognize that some aspects of eye tracking analysis have been investigated to a lesser degree than others.

The column for the category “interactive visualization” shows that there are not many visualizations for interactive analysis of eye tracking data. Most visualizations follow the paradigm of static visualization and provide little support for interaction. For this reason, we motivate to allow more user interaction with visualization techniques for eye tracking data. Interaction allows the user to investigate the data by using filtering techniques or selecting participants.

Table 1 also shows that the number of spatio-temporal visualization techniques for AOI-based analysis is small. Usually, if time is visualized for AOI-based methods, a timeline is used along with one other data dimension. Therefore, animation is not needed. This might also explain the lack of in-context visualization techniques for AOI-based analysis. In case of point-based eye tracking visualizations, fixation data is often overlaid on the stimulus or presented as a 3D visualization in case of dynamic stimuli. For in-context AOI-based visualization, the presentation of the eye tracking data is more abstract. This abstraction is intended to help analysts concentrate on specific semantic questions. However, the mental map of the eye tracking data on the stimulus is lost.

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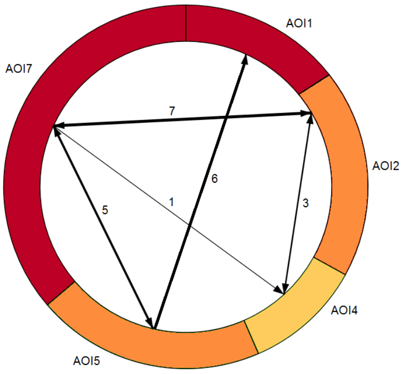


**Figure 21:** *The circular heat map transition diagram places AOIs on a circle, where the AOI circle segment is color-coded based on the fixation count inside the AOI. The size of the circle segment indicates the total dwell time within an AOI. Transitions between AOIs are represented by arrows, with the thickness displaying the number of transitions. Figure based on [BRE13].*

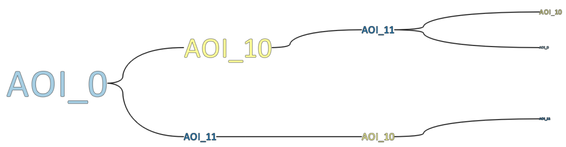


**Figure 22:** *A word tree represents the sequences of AOIs starting at a selected AOI. The font size corresponds to the number of sequences. The sequence AOI 0, AOI 10 and AOI 11, shows the most common sequence amongst participants.*

In general, for AOI-based methods, the biggest limitation is the number of AOIs that can be represented at once. Most of the techniques do not scale well, if there are many AOIs. Here, new visualization techniques have to be developed.

We found that the number of visualization techniques for the category "dynamic stimuli" increased within the last five years. The literature research also showed that the question of how the visual analysis of multiple viewers with an individual stimulus is still an interesting research topic. Application areas for dynamic stimuli are, for example, video data or data coming from a head-mounted eye tracker. Only a few approaches deal with the question of how 3D eye tracking data can be visualized. This question is important in case of user experiments that record stereoscopic fixation data.

Also, separate handling of smooth pursuit from dynamic stimuli has mostly been neglected. Including smooth pursuit information in scanpath representations, for example, could provide valuable information about attentional synchrony behavior of multiple viewers.

Furthermore, we think that multimodal data visualization techniques will become more important due to the interdisciplinary character of eye tracking research. For example, eye tracking data could be combined with other sensor information coming from EEG devices, or skin-resistance measurements. One approach is already included in the commercial software BeGaze from SMI [SMI14]. However, there are many open questions for new visualizations techniques in this direction.

Another challenge in eye tracking are stimuli with active content, where the user can influence the stimulus during the study. For example, in studies of the usability of Web pages, users may click on links and navigate to different sites. Here, the question is how participants can be compared. Often, a representative stimulus is created and the fixation of the participants are manually mapped to the stimulus. However, this might lead to erroneous data due to ambiguity or inaccuracies introduced by the annotator. A tool called Gaze Tracker [Lan00] records the complete Web page information and scroll behavior automatically. Yet, this approach can only be used for Web pages or graphical user interfaces. We believe that further visualization techniques for this type of stimulus will be developed in the future.

Our literature review showed that there is a large number of visualization techniques for the analysis of eye tracking data. However, it is not always apparent which visualization technique works best for which type of analysis. This question cannot be answered completely and to a full extent. Choosing an appropriate visualization technique depends on different factors. Therefore, we have classified the presented techniques based on our taxonomy. Yet, we have let out the analysis task. For example, a common analysis task is to compare scanpaths of participants. Comparing scanpaths of multiple users can help find regularities or similar patterns between different participants. Many of the presented visualization techniques can be used for scanpath comparison [Coc09, GH10b, TTS10, WHRK06, RHOL13, RBB14]. This is just one example of how the analysis task influences the type of visualization technique for an evaluation.

Finding patterns in the eye tracking data is a general goal of eye tracking analysis. However, often not one visualization technique alone is sufficient to find those patterns and analyze the eye tracking data. Rather, multiple visualization techniques have to be used in combination. An interaction of the user with the visualization techniques can further improve analysis results. In the end, statistical tests have to be used to show that results are significant. Therefore, we propose to combine those approaches: using visualizations, statistics, and interaction together. This is to some extend done by visual analytics and could therefore, also be applied to eye tracking analysis.

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## 7. Conclusion

In this state-of-the-art report, we have reviewed existing papers describing eye tracking visualizations. To classify the different approaches we have created a taxonomy that divides the papers into point-based and AOI-based visualization techniques as well as into visualizations that use both types of data. Furthermore, we have classified the papers on the second level according to the data represented: temporal, spatial, or spatio-temporal. An overview of all visualization techniques was given as well as a detailed description of the different visualization techniques. Based on the results, we have presented future directions for research.

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