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AOI Rivers for Visualizing Dynamic Eye Gaze Frequencies

Michael Burch, Andreas Kull, and Daniel Weiskopf

VISUS, University of Stuttgart, Germany

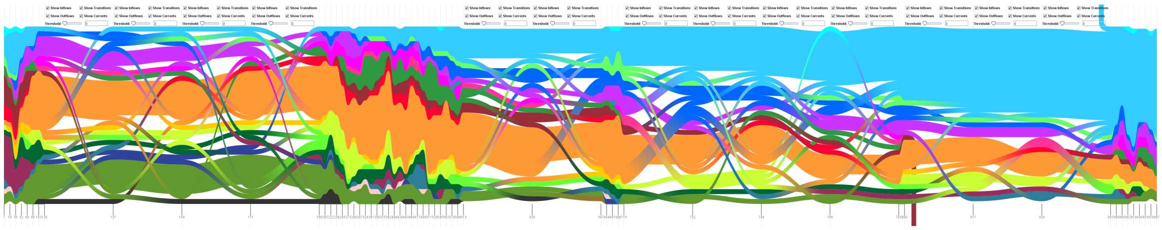


Figure 1: *Visualizing time-varying frequencies of eye gaze fixations and transitions with AOI Rivers.*

Abstract

It is difficult to explore and analyze eye gaze trajectories for commonly applied visual task solution strategies because such data shows complex spatio-temporal structure. In particular, the traditional eye gaze plots of scan paths fail for a large number of study participants since these plots lead to much visual clutter. To address this problem we introduce the AOI Rivers technique as a novel interactive visualization method for investigating time-varying fixation frequencies, transitions between areas of interest (AOIs), and the sequential order of gaze visits to AOIs in a visual stimulus of an eye tracking experiment. To this end, we extend the ThemeRiver technique by influents, effluents, and transitions similar to the concept of Sankey diagrams. The AOI Rivers visualization is complemented by linked spatial views of the data in the form of heatmaps, gaze plots, or display of the visual stimulus. The usefulness of our technique is demonstrated for gaze trajectory data recorded in a previously conducted eye tracking experiment.

Categories and Subject Descriptors (according to ACM CCS): H.5.0 [Information Interfaces and Presentation]: General—

1. Introduction

Eye tracking is a powerful instrument to investigate people's eye movement behavior when visually exploring a given stimulus on a computer screen. In our research community, many controlled user studies have been conducted to obtain insights in exploration processes when users work with visualization techniques to be assessed. As standard practice, user performance is measured, recorded, and evaluated aiming at understanding the benefits and drawbacks of visualizations by testing accuracies and completion times for statistical significance. Eye tracking experiments add the gaze trajectories data to the analysis process as another dependent variable to be investigated. Only by exploring the vast amount of eye movement data, we are able to understand visual task solution strategies, identify the impact of independent variables on those strategies, and confirm or reject the hypotheses related to task solution strategies.

There is no general technical limit for the amount of data recorded during eye tracking experiments. The biggest challenge is the analysis of the vast amount of spatio-temporal data produced in the form of eye gaze trajectories. Typically, an eye tracking system already provides integrated visualization techniques that allow visual exploration of the recorded data, but these visualization techniques come with limitations caused by aggregation in space and time as well as overplotting and visual clutter [RLMJ05]. In this work, we present a novel visualization technique that addresses the shortcomings of traditional heatmap representations and gaze plots, which are the basic data visualization methods integrated into today's eye tracking systems.

The heatmap provides a time- and participant-aggregated visualization of fixation densities. In such a diagram, the information is lost which parts—areas of interest (AOIs)—were inspected in which sequential order. In contrast, the gaze plot shows this sequential order. However, by displaying all eye gaze trajectories as color-coded polylines on top of each other, the gaze plot results in visual clutter and, hence, difficulties in identifying the sequential order and the additional time-varying gaze frequencies. Therefore, an alternative representation of the dynamic gaze frequency data is needed to show the evolving gaze patterns, their frequencies, and a mapping to the spatial context of corresponding AOIs.

With these goals in mind, we introduce the concept of AOI Rivers: a visualization technique that takes into account the time-varying behavior, the transitions, and the sequential order of frequently visited regions of a stimulus. Figure 1 shows an example of AOI Rivers. As a benefit of our technique, AOIs can be defined on user's demand, leading to an automatically updated representation that illustrates the number of fixations in the AOIs over time. The AOI Rivers are based on the ThemeRiver representation [HHWN02]; the novel technical contribution is the enhancement of the ThemeRiver representation by splitting and merging subrivers (similar to the concept of Sankey diagrams [Tuf83]) and the extension by influents and effluents. These enhancements are designed for eye tracking analysis: they allow us to show the information about how many participants moved their eyes from one AOI to another and at what time; they also allow us to investigate eye gazes that are not assigned to any of the specified AOIs or leave the display.

AOI Rivers allow the user to investigate important aspects that are relevant for eye tracking trajectory data:

- **Durations of AOI visits:** The time-varying behavior of AOI visits can be explored by inspecting the rivers visible in time intervals of interest.
- **Frequency of AOI visits:** Inspecting the varying thicknesses of the single rivers provides information about the evolving fixation frequencies.
- **Transitions between AOIs:** By looking at the splitting and merging behavior as well as influents and effluents, the viewer can inspect the relative number of study participants that move their eyes between the respective AOIs over time.
- **Sequential order of AOI visits:** The viewer is also able to visually analyze the sequential order of two subsequently visited AOIs in combination with their frequencies. Understanding the sequential order of long AOI sequences is difficult by a static picture alone due to merging and splitting but can be handled with interactive exploration.

The splitting and merging behavior can be investigated in detail to find out how and where new rivers originate and which other rivers and subrivers affect the behavior over time. A similar exploration can be conducted by looking for rivers that have disappeared and how they split into subrivers, leading to a possible increase of frequency in other rivers.

In our visualization, the spatial information about AOIs is not directly represented like in heatmaps or gaze plots. In fact, the very design goal of AOI Rivers is to provide a complementary, abstract, and time-oriented view on the data. The spatial context is included by linking the AOI Rivers with additional spatial views in the form of heatmaps, gaze plots, or just the display for the stimulus. Typically, only a small number of AOIs are annotated for a given stimulus by text labels and this textual information as well as AOI color coding can be used to link the AOI Rivers to their spatial location in the stimulus.

We illustrate the usefulness of the AOI Rivers visualization by applying it to eye gaze data recorded in a previously conducted eye tracking study [BKH*11]; this dataset is publicly available [AABW12a]. We show that our visualization technique allows us to gain insights in the spatiotemporal trajectories that confirm previous results from the same dataset [AABW12b, BKH*11, BAA*13] and that novel findings can be uncovered.

2. Related Work

Evaluation based on eye tracking is an emerging subfield in visualization in general and information visualization in particular, see for example [BBBD08]. The main challenge for eye tracking is not the actual experiment or recording of the data but the analysis of the large number of trajectories. Recently, Andrienko et al. [AABW12b] have proposed a visual analytics methodology for exploring eye tracking data based on different visualization and statistical techniques. They discuss shortcomings of the commonly applied visualization and analysis techniques for eye tracking.

We follow their line of reasoning and further enhance the repertoire of visual analysis methods by introducing AOI Rivers. Although Andrienko et al. [AABW12b] cover a wide range of methods, they do not discuss any methods related to Sankey diagrams showing the time-varying frequencies of visited AOIs. With this paper, we want to fill this gap. As benchmark and for comparison, we use the same dataset from a previous eye tracking experiment [BKH*11] that was also used by Andrienko et al. [AABW12b] and in the detailed follow-up analysis by Burch et al. [BAA*13].

Generally, eye tracking data is displayed by time- and participant-aggregated representations in the form of heatmaps [Boj09, PRV96, SM07, Woo02] or by line-based renderings in gaze plots [CFL10, ETT*08, GH10, Lan00, RAM*05]. However, neither concept can show the time-varying frequencies of gaze fixations that would be needed to gain insights into the common behavior of participants when moving their eyes from one user-defined AOI to another in a stimulus. For this reason, AOI transitions are often investigated [IHN98, WHRK06], but typically only the transitions between two subsequent time points are shown. In contrast, a river-like metaphor—such as in AOI Rivers—would help show longer time sequences as a continuous flow.

More recent approaches to analyzing search strategies in eye tracking data are facilitated by eSeeTrack [TTS10]. This tool provides a tree-like diagram to show subsequences of previously annotated visual elements in a sequential order. Neither time nor space is explicitly shown in the diagram, whereas AOI Rivers encode time explicitly. Raschke et al. [RCE12] generated parallel scan paths for an impression of commonly applied eye movements. However, when the number of study participants increases, visual clutter also occurs in the parallel scan paths. Line-based representations are to blame for this shortcoming, whereas in AOI Rivers common scan paths are aggregated in rivers of different thickness. Furthermore, the distribution of fixation frequencies and their sources and sinks are not explicitly shown in parallel scan paths but in AOI Rivers.

The recent work by Boyandin et al. [BBBL11] on Flowstrates addresses the generic visualization of temporal origin–destination data. If this approach was adapted to eye tracking data, it would allow us to show AOI transitions, influents, and effluents by temporal heatmaps. By using two separate maps, a direct linking to the spatial information would be possible. However, our AOI Rivers scale better for many timesteps with many transitions and they show quantitative data of fixation frequencies by the thickness of rivers, which is more accurately perceived than by color coding in temporal heatmaps.

The AOI Rivers technique is based on the concept of Sankey diagrams [Tuf83] showing time-varying quantities as well as their splitting and merging behavior. A famous early example of this type of visualization goes back to Charles Joseph Minard [Min61], who illustrated the march of Napoleon's army to Moscow and their retreat—also called a flow map. In his work, time is visualized by decreasing thickness, color coding (advance and retreat), and following the river beginning from the starting point and heading back again. In our work, we introduce an explicit timeline to the technique of Sankey diagrams to show the evolving splitting and merging behavior of quantities over time. Related to our work is the interactive Sankey diagram by Riehmann et al. [RHF05], used to visualize the energy flow in a city. However, they did not use a smooth transformation of color for the subrivers and they did not design it for the analysis of eye gaze frequencies.

The ThemeRiver technique [HHWN02] is most related to ours: it meets many of the requirements for showing time-dependent gaze data. We enhance the ThemeRiver technique by extending it with influents, effluents, and transitions exploiting color coding and varying thicknesses. In this way, the AOI Rivers support an analyst in exploring eye tracking data in a more time-based non-aggregated and uncluttered way than heatmaps or gaze plots would offer. There are other extensions of ThemeRiver. One example is TextFlow [CLT*11]: a system for analyzing theme evolution in text data. In that technique, correlations between tags can be displayed and how events bring new topics to life. Another example is RankExplorer [SCL*12], which allows one to additionally analyze changes in a ThemeRiver visualization. None of these ThemeRiver variants shows the extensions of AOI Rivers or target eye tracking data.

We base AOI Rivers on the Visual Information Seeking Mantra [Shn96]: overview first, zoom and filter, then details on demand. A traditional ThemeRiver representation is used to provide an overview of frequently visited AOIs over time. Then, zoom and filter allow the user to explore splitting and merging behavior as well as influents and effluents. Details on demand can be applied to all presented rivers showing the actual quantities and raw data in its textual form.

3. Data Model and Transformations

We model a trajectory T as a sequence of $n \in \mathbb{N}$ points:

$$T := p_1 \to p_2 \to \ldots \to p_n ,$$

where $p_i := (p_{x_i}, p_{y_i}) \in \mathbb{N} \times \mathbb{N}$. Each p_i is associated with two timestamps $t_{e_i} \in \mathbb{N}$ and $t_{l_i} \in \mathbb{N}$, where

$$t_{e_i} < t_{l_i} < t_{e_{i+1}} \ \forall i \in \mathbb{N} : 1 \leq i \leq n-1 .$$

At time t_{e_i}, the eye first enters the point p_i; and at time t_{l_i}, it leaves the point again. The timestamps are modeled as milliseconds starting from January 1st, 1970. In this way, we can divide each trajectory into a number of time-based segments containing time periods for visited points and time periods for moving the eye from one fixation to another. The total time taken to produce a trajectory can be expressed as

$$t := \sum_{i=1}^{n} (t_{l_i} - t_{e_i}) + \sum_{i=1}^{n-1} (t_{e_{i+1}} - t_{l_i}) ,$$

which refers to traditional task completion time t. We denote $t_{l_i} - t_{e_i} =: t_{d_i}$ as gaze duration at point p_i and $t_{e_{i+1}} - t_{l_i} =: t_{m_i}$ as eye movement duration between points p_i and p_{i+1}.

We use the notation

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

for modeling a set of $m \in \mathbb{N}$ trajectories. A single trajectory is expressed as a sequence of fixations:

$$T_i := p_{i,1} \to p_{i,2} \to \ldots \to p_{i,n_i},\ 1 \leq i \leq m .$$

Trajectory sequences T_i may differ in their length n_i. Furthermore, $p_{i,j}$ refers to point j in trajectory i.

3.1. Trajectory Normalization

Participants in user studies do not perform equally well. Some of them take more time to answer a given task than others, which can result in widely spread task completion times that are typically averaged and statistically evaluated.

In our approach, we often apply an alignment of start and end times to temporally normalize the trajectory data. We find this a useful transformation strategy because participants typically start at a well-defined point in time (i.e., when they start inspecting the displayed stimulus) and end at a well-defined point in time (i.e., when they find the solution to the task). In general, we do not necessarily need to transform the trajectory data (for example, when there is no common end solution). The AOI Rivers work equally well for non-normalized trajectories. As discussed by Andrienko et al. [AABW12b], temporal normalization to constant time spans is especially useful when scan paths are based on well-defined start and end events. The example data from the eye tracking experiment [BKH*11] is a typical case for such normalization because the task of that study had a well-defined target that the users had to find and that also determined the end of the eye gaze trajectory.

If the trajectory data $\mathbb{T}$ is normalized, we first make it zero-based: all trajectories start at time 0, i.e., from all t_{e_i} and t_{l_i} we subtract t_{e_1} obtaining $\overline{t_{e_i}} := t_{e_i} - t_{e_1}$ and $\overline{t_{l_i}} := t_{l_i} - t_{e_1}$. Then, all $\overline{t_{e_i}}, \overline{t_{l_i}}$ are divided by the task completion time t for this trajectory T_i and are then multiplied by 1,000 units each, which leads to equally long normalized trajectories of equal length of 1,000 units each:

$$\tilde{t_{e_i}} := \frac{1000 \cdot \overline{t_{e_i}}}{t} \ units$$

and

$$\tilde{t_{l_i}} := \frac{1000 \cdot \overline{t_{l_i}}}{t} \ units \ .$$

We model the set of normalized trajectories as $\tilde{\mathbb{T}}$.

3.2. AOIs, Transition Matrices, and Aggregation

We define an area of interest A as a region in the displayed stimulus that is not necessarily rectangular. This region is mathematically modeled as a connected set of discrete points in the display

$$A \subseteq \mathbb{N} \times \mathbb{N} \ .$$

The set of all k defined AOIs in a stimulus is modeled as

$$\mathbb{A} := \{A_1, \ldots, A_k\} \ .$$

Generally, overlaps among the AOIs are allowed, i.e., we may have

$$A_i \cap A_j \neq \emptyset \ , \ \text{with } 1 \leq i, j \leq k \ .$$

In this case, Algorithm 1 has to use sets of indices for the source and target AOIs instead of single numbers and the matrices have to updated for all pairs of elements out of those sets for the corresponding time units.

From these AOIs $\mathbb{A}$ and the set of trajectories $\mathbb{T}$ or normalized trajectories $\tilde{\mathbb{T}}$, the time-varying transition matrices

$$M_j \in M(k+1 \times k+1, \mathbb{N})$$

can be computed. It may be noteworthy that we need one more AOI here for also computing visits that lie not inside any of the AOIs (for influents and effluents).

First, the maximum length of all trajectories is computed. In case of the normalized $\tilde{\mathbb{T}}$, the maximum length is 1,000 units by construction. For non-normalized trajectories, that length is given by the largest completion time t_{max} of all trajectories. This t_{max} is then divided into equally long time units.

As a second step, each trajectory is processed for all time units one-by-one and it is checked if the visited point at this unit is located inside one of the AOIs $\mathbb{A}$. If AOI A_s is visited at time unit $j \in \mathbb{N}$ and AOI A_t is visited at unit $j+1$, then $M_j[s][t]$ is incremented by one. Doing this for all trajectories on a unit basis, we obtain t_{max} many transition matrices that can be used to visualize dynamic eye gaze frequencies as well as influents, effluents, and transitions. Algorithm 1 shows the pseudo code for the generation process of a sequence of transition matrices from a set of trajectories $\mathbb{T}$ and a set of pre-defined AOIs $\mathbb{A}$.

Algorithm 1 Generation of Transition Matrices

```
TransMatGen(𝕋, 𝔸):
  // 𝕋: Set of trajectories
  // 𝔸: Set of AOIs
  // 𝕄: Sequence of matrices
  m := size(𝕋);
  k := size(𝔸);
  for i := 1 to m do
    l_i := length(T_i);           // Units of i-th trajectory
    for j := 1 to l_i − 1 do
      s := k + 1;                 // Index of source AOI
      t := k + 1;                 // Index of target AOI
      for l := 1 to k do
        if p_{i,j} ∈ A_l then
          s := l;                 // If point inside AOI
        end if
        if p_{i,j+1} ∈ A_l then
          t := l;                 // If point inside AOI
        end if
        𝕄_j[s][t] + +;            // Increment matrix entry
      end for
    end for
  end for
  return 𝕄;                       // Transition matrices 𝕄
```

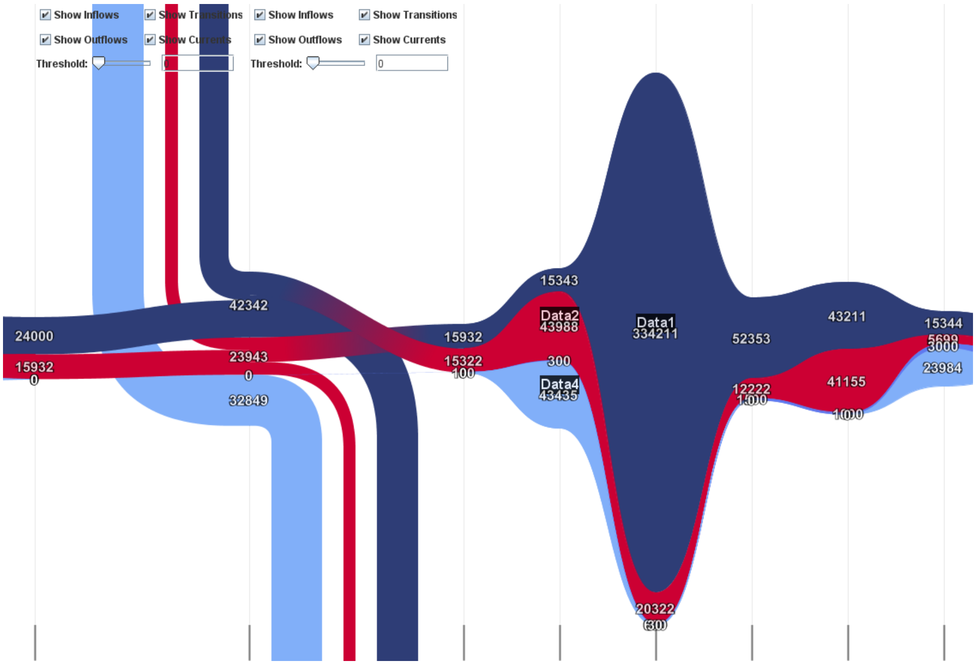


Figure 2: *Visual encoding of time-varying eye gaze frequencies as AOI Rivers.*

Our data model allows aggregation for trajectories, AOIs, and also the time dimension. Trajectories are already aggregated by the transition matrices generation. An aggregation of several AOIs means summing up corresponding rows and columns in each of the transition matrices. An aggregation of several subsequent time units means that all corresponding subsequent transition matrices are summed up.

4. Visualization Technique

Trajectory data for a specific stimulus is first preprocessed depending on the user-defined AOIs $\mathbb{A}$. In this preprocessing step, time-varying quantities for all AOIs and their transition matrices between subsequent time units are generated, see Algorithm 1. This derived information is then used to apply the concept of AOI Rivers: a Sankey diagram-like representation allowing for influents, effluents, and transitions whose visual components, algorithmic details, and interaction techniques will be explained in the following subsections.

4.1. Visual Encoding

The spatiotemporal trajectory data is visually encoded as explained below and illustrated in Figure 2:

- **Single AOI:** A single area of interest A_i can be regarded as categorical data and is visualized as a color-coded river according to the ThemeRiver and Sankey diagram metaphor.
- **Eye gaze frequency:** The frequency of visits at a specific time unit j in the corresponding AOI A_i is denoted by

$$freq_{j,i} := \sum_{l=1}^{k+1} M_j[i][l]$$

  and is visually encoded as the thickness relative to the maximum AOI frequency sum computed over all time units.
- **Sequential order of AOIs:** The traditional ThemeRiver technique only allows us to explore time-varying frequencies, but it remains unclear from where changes among those frequencies result. To facilitate the inspection of these phenomena we integrate splitting and merging subrivers to the ThemeRiver metaphor similar to Sankey diagrams, i.e., we show the transitions $M_j[s][t]$ from sources s to targets t for the specific time unit j.
- **Eye gazes outside AOIs:** All eye gazes that are not directly inside an AOI but leave one or come into one later on are displayed as effluents and influents. Effluents point orthogonally toward the bottom of the screen, whereas influents come from the top and orthogonally merge into the corresponding river. Our model follows the natural flow governed by gravity. Effluents from a source s at time unit j are stored in $M_j[s][k+1]$, whereas influents to a target AOI indexed by t are stored in $M_j[k+1][t]$.
- **Time dimension:** The temporal order of single timesteps (i.e., time units) is visualized as in the traditional ThemeRiver representation with left-to-right reading direction. Each time unit is given the same horizontal space.

4.2. Representation of AOI Rivers

For the representation of AOI Rivers, we first use a stacked representation of the single time-varying quantities. We do not map the values to a common base line but use a symmetric mapping around a horizontal line instead for aesthetic reasons. Initially, we use the same order for the stacking as given by the order in the dataset, i.e., as the rows of the transition matrices $\mathbb{M}$. Similar to the original ThemeRiver, we use interpolation to achieve a connected curved outline for each time-varying quantity. Apart from an aesthetic quality of the visualization, also a realistic mapping of the data has to be computed.

We follow Havre et al. [HHWN02] for computing the interpolation. The interpolation uses cubic Bézier curves as in the ThemeRiver approach. Then, the control points P_0 and P_3 at the start and end of the cubic Bézier curve are given by the respective points that are to be interpolated. We denote the coordinates of point P_i by (x_i, y_i). Then, for the coordinates of the points P_1 and P_2, we obtain: $y_1 := y_0$, $y_2 := y_3$, and $x_1 = x_2 := \frac{(x_3+x_0)}{2}$. This leads to horizontal tangent vectors at the interpolation points.

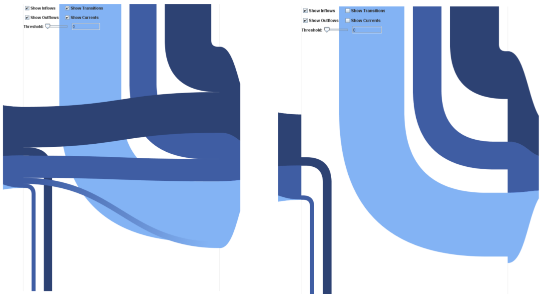
4.3. Influents, Effluents, and AOI Transitions

The representation of influents, effluents, and AOI transitions is based on the concept also used in Sankey diagrams. Figure 2 shows a part of an AOI Rivers representation illustrating influents, effluents, and AOI transitions. At the top, there are checkboxes and a slider to interactively change the visualization with respect to certain parameters such as a threshold slider or checkboxes for influents, effluents, transitions, and currents. This interactive feature can be applied for the rivers between subsequent time units, see also Figure 3.

We visually encode influents starting from top orthogonally to the main rivers and merging at the point in time to their corresponding main rivers. Analogously, effluents are represented by splitting off at the corresponding point in time and pointing orthogonally to the bottom.

The order of representation of single subrivers is computed in a way that even for many influents and effluents, all transitions remain recognizable. Influents and effluents typically cross several of the represented transitions. Therefore, we draw them in the background. In contrast, the transitions are rendered in the foreground. Another reason for this design choice comes from the fact that, for influents and effluents, only the frequency but not the further evolution plays a critical role for interpreting the data. This can be seen at the upper (influent) or lower (effluent) border of the display.

For transitions, we distinguish between those to the same river and those between two different rivers. The latter ones are displayed by a linear color gradient interpolating between the two colors of the start and destination rivers. To avoid occlusion of such transitions between two different rivers our algorithm places them to the foreground.



(a) (b)

Figure 3: *AOI Rivers for a small example dataset: (a) All influents, effluents, and AOI transitions are displayed. (b) Filtered representation for illustrating the order of influents and effluents in the AOI Rivers (the same data as in (a)).*

To further avoid crossings of single influents or effluents in the visualization we choose a left-to-right order for both. For main rivers located closer to the bottom, the corresponding influents and effluents are placed more to the left, see Figure 3 (a). In Figure 3 (b), a filtered representation is used: all transitions are invisible and only influents and effluents are explicitly represented.

When a river splits into an effluent and several transitions or a river merges from an influent and several transitions, we define a vertical order in such a river: first, the influents are drawn, then the transitions between the same river and the transitions between two different rivers, and finally the effluents.

If the number of rivers is too large and there are many split and merge events between two subsequent time units, we allow interactive filtering that can be applied to each gap between two time units separately. The user can choose if influents, effluents, transitions, or the main currents are displayed. Furthermore, the user can move a slider to change the minimum value for the frequency for which a river is visualized.

4.4. River Color Coding

Color coding for the AOI Rivers has to take into account several different objectives. On the one hand, the colors for the rivers should look aesthetically pleasing and should be harmonic. On the other hand, the contrast of colors should be large enough to make neighboring rivers easy to distinguish. In the scenario of AOI Rivers, we allow transitions, i.e., merging and splitting behaviors, resulting in the problem that formerly distant rivers may become closer or even neighbors after several timesteps. This might lead to similarly colored rivers being located close to each other. Furthermore, the color contrast of all rivers that have a transition between each other should be large enough to make this transition visible. Addressing this problem by computing an optimal color map is challenging and belongs to the class of intractable problems [GJ79].

In our implementation of AOI Rivers, we support the analyst by three different options for color coding:

- A heuristic approach for computing an automatic color coding for all displayed rivers can be used. In this algorithm, we target an equal distribution of colors from the given color space, adopting the algorithm by Ankerl [Ank09]. The computation is based on the HSB color space, in which colors are defined by their hue, saturation, and brightness. Saturation and brightness are fixed to a constant value; the different colors of the rivers only differ by their hue value.
- Another approach for color coding is to use a totally random selection of colors or to randomly select colors from a pre-defined list of colors. Since there are typically only a small number of different rivers (because only a small number of AOIs is worth investigating), this strategy also leads to a good color coding.
- The user can manually choose colors for the individual AOI rivers.

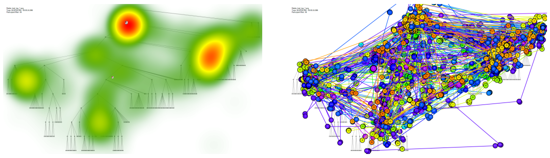
4.5. Annotation by Text Labels

For the labeling of data values and rivers, we use two different types of representations. To facilitate good readability of the text labels a strong contrast to the background color of the river representation must be achieved. For this reason, we choose a text in white color for both text label types: in one case surrounded by black contours, in the other case with a filled rectangle as background region. For data values, we use the contour representation and for river annotations we use the semi-transparent black colored rectangle with white text on top of it.

Data value labels are placed in the center of a river at the respective time unit and value. The evolution of the rivers is also illustrated by the textual information. The static display of the river labels is at the position where the river thickness is maximal. If there are several possible positions with the same thickness, we place the text labels at the leftmost position in the AOI Rivers.

4.6. Implementation

Our implementation is based on the Java programming language. The technical components described above can be mapped in a straightforward way to a Java implementation. Here, we only briefly discuss a few technical aspects. For rendering, the cubic Bézier curves are drawn with CubicCurve2D of the Java API. From the horizontally neighboring curves of the AOI Rivers, we compute a list of tiles by using the Java class Area that serves as the basis for rendering. By precomputating the AOI river labels, we achieve sufficiently high visualization speed as to guarantee smooth interaction with the visualization for typical datasets, including the one used in our case study.



(a) (b)

Figure 4: *Visualization techniques integrated into eye tracking systems: (a) Time- and participant-aggregated heatmap. (b) Line-based gaze plot affected by visual clutter.*

5. Case Study

In this case study, we investigate large trajectory-based data from a previously conducted eye tracking experiment focusing on the readability of different node-link tree diagrams [BKH*11]. The data in its raw form is publicly available [AABW12a]. Before using the data, we had to preprocess it to transform it to our tool-specific format, i.e., user-defined AOIs are used to derive time-varying frequencies of AOI visits and all pairwise transitions between AOIs over time, see Algorithm 1. The raw data remains accessible to support the analyst by details-on-demand information when interactively working with the AOI Rivers technique.

Figure 4 (a) illustrates a heatmap representation of the eye gaze data, only showing the hot spots displayed on top of the presented stimulus in the eye tracking study. In such a diagram, we can only find out where the participants looked frequently, aggregated over time. The sequential order and time-varying frequencies cannot be explored with such a diagram. In Figure 4 (b), a gaze plot is used to illustrate the trajectories of each participant in different color-coded polylines. This overplotted line-based diagram results in visual clutter and hence, in difficulties in deriving the sequential order of frequent visits over time.

In the following, we illustrate how to apply the AOI Rivers technique to the same data as used in Figure 4. In particular, we used the eye tracking trajectories for the stimulus showing a node-link tree diagram in a traditional layout with the root node on top and with three marked leaf nodes. The study participants had to find the least common ancestor of the marked leaf nodes and had to confirm it by a mouse click. For more details on the original study and task, we refer to Burch et al. [BKH*11].

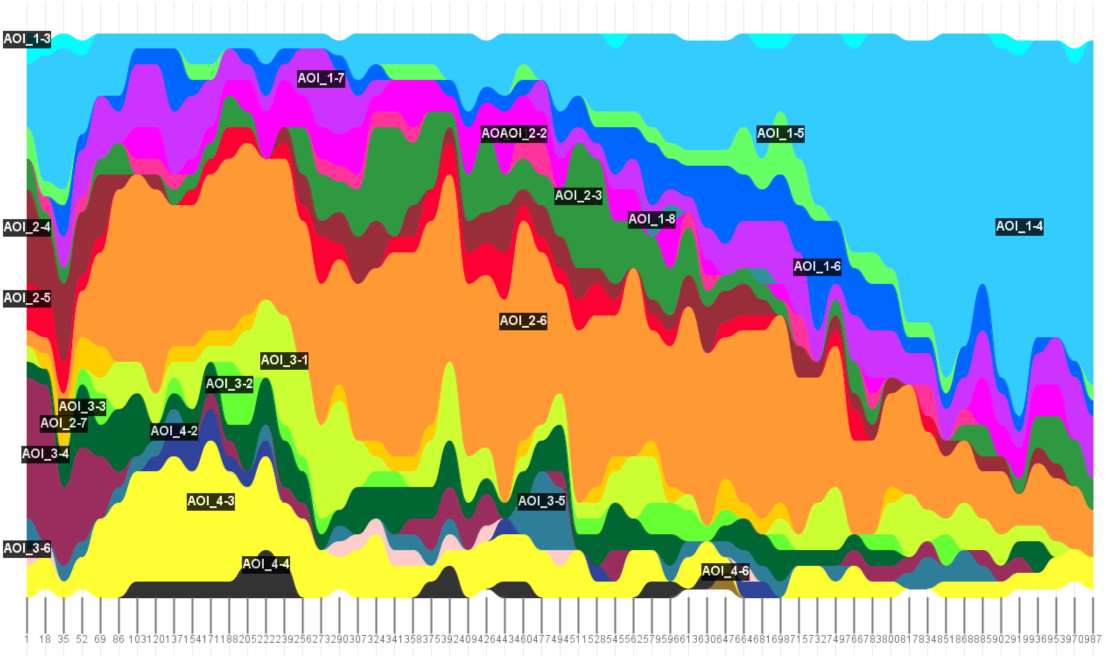


Figure 5: *AOI Rivers for the eye gaze trajectory data from the stimulus shown in Figure 4.*

5.1. Defining Areas of Interest

Figure 4 shows the visual stimulus with an overlay of a heatmap (a) and a gaze plot (b). In general, one can use the semantics of the displayed stimulus to define AOIs. In the example node-link diagram, the root node, inner nodes, solution node, and marked leaf nodes describe such semantic information of associated AOIs.

In our tool, we are able to select AOIs that enclose such points of interest as it was done in the original study evaluation. However, we are also able to explore the complete display space; hence, in the following we divide the stimulus into 32 non-overlapping AOIs in a grid-like manner. The AOIs are numbered by A_{i-j}, where i expresses the row at which it is located and j the corresponding column.

Figure 5 shows the time-varying eye gaze frequencies for normalized trajectories divided into 1,000 time units from the eye tracking study annotated with the AOI labels. The time units are displayed at the bottom of the figure. For this figure, we used time unit aggregation and summed up each 17 subsequent transition matrices (can be changed on user's demand). Each AOI is color-coded by randomly attaching colors from a pre-defined list of colors taken from ColorBrewer [BHT09]. It may be noted that some AOIs are not present in Figure 5 because the number of visits is very small or even zero, which is our first insight in the data.

5.2. ThemeRiver Representation

From the traditional ThemeRiver in Figure 5, we can already derive that in the beginning, there is no substantial difference in frequency of visits to different AOIs. This can be interpreted as that participants get an overview about the complete stimulus. However, as time goes by, many study participants look at AOI A_{2-6} (orange) and AOI A_{4-3} (yellow) more frequently than at any other AOI. Comparing this to the shown stimulus, we find out that these AOIs belong to the leftmost marked leaf node (AOI A_{2-6}) and the marked leaf node in the center (AOI A_{4-3}). This means that the study participants frequently inspected the leaf nodes in the beginning of the exploration process, which is necessary to perform the given task correctly.

Toward the end of the exploration, the largest portion of participants inspected AOIs in the top row, i.e., AOIs numbered A_{1-j}, where AOI A_{1-4} is visited most frequently by the study participants. Looking again in the displayed stimulus, we see that the solution node is located in AOI A_{1-4}, which shows us that most of the participants finished this task by looking at the correct solution node.

5.3. Inspecting AOI Transitions

The traditional ThemeRiver can only give an overview of the time-varying eye gaze frequencies for user-defined AOIs. However, by this visualization, we are not able to see influents, effluents, or AOI transitions that are needed to understand from which AOIs eye gazes come and where they

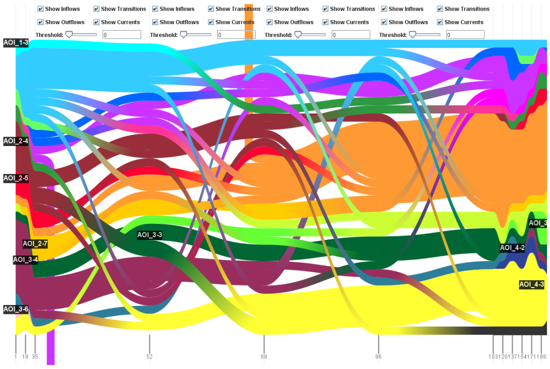


Figure 6: *Exploration of AOI transitions in the beginning phase for AOIs A_{2-6} and A_{4-3}.*

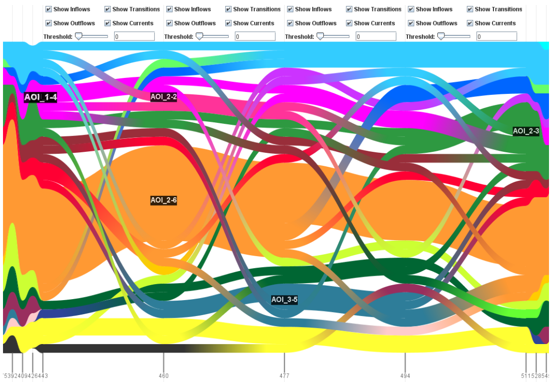


Figure 7: *AOI A_{3-5} is visited frequently in a short time interval and then split into several other rivers.*

move. AOI Rivers can be used to interactively look between two subsequent time units to visually analyze the eye movement behavior of a number of study participants.

Figure 6 helps understand from which other AOIs the study participants move their eyes to the more frequently visited AOIs A_{2-6} (orange) and A_{4-3} (yellow). Furthermore, we can see that AOI A_{3-4} (dark magenta) is completely split into several other AOIs, i.e., it was inspected in the beginning but was only of little interest for further inspection at later times.

When we have a look at AOI A_{3-5} in Figure 5, we can see that it is visited frequently only for a short time (from time unit 443 until 511). Figure 7 shows from which AOIs the study participants come when visiting AOI A_{3-5} and in which AOIs it is split again.

AOI A_{1-4} is the most frequently visited AOI in the end of the exploration process. However, also here an anomaly can be detected. There is a peak that shows that participants do not confirm the task solution directly but move their eyes to other AOIs and come back later again. In Figure 8, we

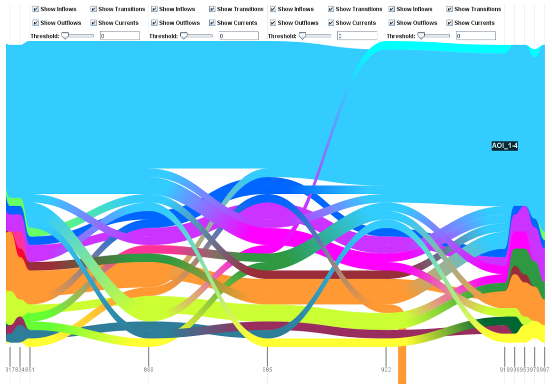


Figure 8: *AOI A_{1-4} contains the correct solution node. In the end, it is the most frequently visited AOI, but many participants look away and then back again.*

can identify the AOIs to which people move their eye gazes before coming back again.

This case study shows a small portion of the insights found in the data and just serves as an illustration for the usefulness of the AOI Rivers technique. This study allowed us to confirm previous findings for this dataset [BKH*11, BAA*13, AABW12b] but with other visual means and, thus, from a different "perspective". This study also allowed us to refine and improve our findings related to the temporal evolution of AOI visits.

6. Conclusion and Future Work

In this paper, we presented AOI Rivers—a novel visualization technique designed to analyze frequencies of eye gaze fixations in user-defined areas of interest. Instead of exploring recorded eye tracking data by time- and participant-aggregated heatmap representations or overplotted line-based gaze plots, we show the trajectory data as time-varying river-like structures enriched by influents, effluents, and AOI transitions similar to Sankey diagrams. To incorporate spatial context, the AOI Rivers are linked to space-oriented displays of the stimulus or heatmap and gaze plot visualizations by color coding. Interaction techniques allow the user to aggregate AOIs and subsequent time units. The usefulness of our technique has been demonstrated for a dataset acquired from an eye tracking experiment investigating the readability of node-link tree diagrams.

As a possible future work, the integration of the AOI Rivers technique into an existing eye tracking system would be of interest as well as a user study finding out how domain experts perform when analyzing eye gaze trajectories. Furthermore, we will take the vertical order of the rivers into account with the goal to have a more clutter-free representation. Also, better automatic color coding belongs to future work.

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