Saccade Plots

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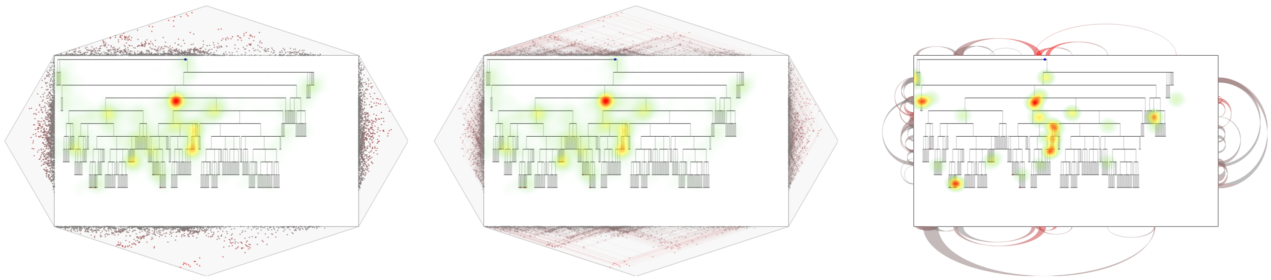

(a) (b) (c)

Figure 1: *Saccade Plots: (a) A pixel-based approach with triangular matrices to achieve visual clutter reduction. (b) A pixel-based approach enriched by guiding lines. (c) An aggregation mode using curved arcs to show the relations.*

Abstract

Visualization by heat maps is a powerful technique for showing frequently visited areas in displayed stimuli. However, by aggregating the spatio-temporal data, heat maps lose the information about the transitions between fixations, i.e., the saccades. In gaze plots, instead, trajectories are shown as overplotted polylines, leading to much visual clutter, which makes those diagrams difficult to read. In this paper, we introduce Saccade Plots as a novel technique that combines the benefits of both approaches: it shows the gaze frequencies as a heat map and the saccades in the form of color-coded triangular matrices that surround the heat map. We illustrate the usefulness of our technique by applying it to a representative example from a previously conducted eye tracking study.

CR Categories: Human-centered computing [Visualization]: Visualization techniques;

Keywords: Eye tracking, saccades, heat maps, adjacency matrices, weighted graphs, information visualization

1 Introduction

Although heat maps provide a good overview of frequently visited regions in a visual stimulus, they lack the visualization of saccade and temporal information. Only the hot spots in the data are visible in a time-aggregated fashion. In contrast, gaze plots show all scan paths in a single static view by overplotted and color-coded polylines. As a drawback, such a representation leads to much visual clutter [Rosenholtz et al. 2005] due to many line crossings.

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We introduce Saccade Plots: a novel approach that shows the original visual stimulus overlaid with a heat map representation surrounded by four triangular matrices that visually encode the saccades as color-coded dots. Those matrices are the key element of our technique. For large data sets from eye tracking studies, the transformation of scan paths into a graph representation results in a dense graph. The denser a graph is, i.e., the more adjacency relations exist, the more visual clutter is generally produced when rendering gaze plots. Matrix representations do not suffer from visual clutter caused by link crossings. Figure 1 (a) shows an example of the triangular matrices, placed around a standard heat map.

The attached triangular matrix representations help the user find out where, when, and how many saccades of specific lengths exist. This overview serves as a starting point in the data exploration process: it can be zoomed in, filtered, and finally details-on-demand can be shown to explore and understand the data.

As a variant of the triangular matrix visualization, we also support the visualization of links between gaze positions in the form of straight lines (Figure 1 (b)) or curved arcs (Figure 1 (c)). These two kinds of representation are especially useful for sparse graphs, i.e., eye tracking data with relatively few or short saccades.

2 Related Work

One of the most prominent visualization techniques in eye tracking research uses attention heat maps [Bojko 2009] that show a time-aggregated view of the number of fixations at specific regions in a stimulus. Although such diagrams are very useful to obtain an overview of frequently visited regions in a stimulus, they lack the visualization of the temporal component, i.e., the time-varying behavior of study participants is lost in such a static display. Evolving heat maps [Poole and Ball 2006] allow the exploration of time-varying eye fixations but do not support the visual analysis of transitions between fixations.

Another visualization technique uses gaze plots to visually encode the spatio-temporal trajectory data by color-coded polylines. Following this concept leads to a phenomenon that visualization researchers denote as visual clutter [Rosenholtz et al. 2005]. Gaze plot visualizations are considered not useful for large data due to much visual clutter [Çöltekin et al. 2010]. As an alternative, Aula et al. [2005] present a non-overlapping scan path visualization technique. A common approach to analyzing eye movement patterns relies on transition matrices [Goldberg and Kotval 1999; Ponsoda et al. 1995]. Another approach to removing visual clutter shown in gaze plots and to exploring the sequential order of visited AOIs is given by eSeeTrack [Tsang et al. 2010]. eSeeTrack combines a timeline with a tree representation to extend current eye tracking visualizations. Durations, frequency, and ordering of fixations are visualized in a combined and linked view.

The AOI Rivers technique [Burch et al. 2013] represents the time-varying eye gaze frequencies as flow maps. Color-coded rivers together with transitions, influents, and effluents allow the exploration of the dynamic AOI visits. The explicit timeline used in the diagram makes the original gaze plot more uncluttered and participant-aggregated. However, the linking to the stimulus must be derived by color coding used for the single AOIs as categorical data. Therefore, the spatial information is lost in AOI Rivers; this problem is addressed by our new technique.

In this paper, we show the heat map representation as an overview. To this context view, we attach saccade plots in form of triangular matrices surrounding the heat map. This design allows a hybrid visualization of the spatio-temporal data: a time-aggregated view as a heat map and a graph-based matrix representation for aggregated movement directions. An important advantage is that we avoid overplotting the stimulus, resulting in reduced visual clutter.

3 Data Model

Eye tracking studies lead to spatio-temporal data in form of trajectories. From those, traditional heat maps can be computed as well as their extension by color-coded triangular matrices expressing the saccades between points and regions of interest.

3.1 Trajectories

We model one trajectory T as a sequence of n points:

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

where $p_i \in \mathbb{N} \times \mathbb{N}$, $1 \leq i \leq n$. Each p_i is associated with two time points $t_{\text{in}_i} \in \mathbb{N}$ and $t_{\text{out}_i} \in \mathbb{N}$, $t_{\text{in}_i} < t_{\text{out}_i} < t_{\text{in}_{i+1}}$, expressing the time of entering a point p_i and the time of leaving it again. From these time points, gaze durations ($t_{\text{out}_i} - t_{\text{in}_i}$) and durations of eye movements ($t_{\text{in}_{i+1}} - t_{\text{out}_i}$) can be derived. Then, the total duration t of a single trajectory T is the sum of the durations of all gazes and eye movements for that trajectory.

The set of all trajectories of m participants recorded for the same stimulus is denoted $\mathbb{T} := \{T_1, \ldots, T_m\}$. Those trajectories generally differ in length, i.e., they contain different numbers of points, which is one reason why the exploration of them is challenging.

3.2 Transformed Trajectories

The set of trajectories $\mathbb{T}$ is transformed into two different data formats. The first one is needed to generate a heat map, whereas the second one is used to produce four types of matrices required to express the saccades.

For the heat map, a two-dimensional array at pixel resolution is computed by taking the gaze durations into account. The time $t_{\text{out}_i} - t_{\text{in}_i}$ spent at point $p_{x,y} := p_i$ is added to the array. Doing this for all trajectories generates a two-dimensional dataset of quantitative values.

We interpret the movement from a start fixation point to a target fixation point as a vector that can be split into its two components:

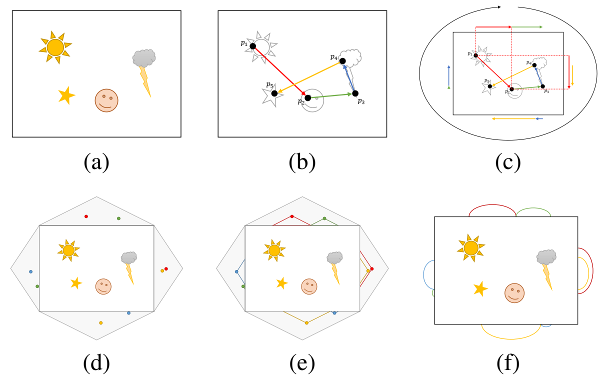

Figure 2: *Transformation into Saccade Plots: (a) Original stimulus. (b) Eye movements. (c) Splitting into x- and y-components for each saccade. (d) Transformation into color-coded dots for clutter reduction. (e) Guiding lines. (f) Curved arcs of different thickness as alternative visual representation.*

the x- and y-directions. Since the positive and negative directions are separated in our visualization, we need four sets of matrices to model these, i.e., movements in the positive x- and y-directions as well as movements in the negative x- and y-directions, see Figure 2. Figure 2 (a) shows an example stimulus. The eye movements recorded are illustrated in Figure 2 (b) as a polyline with color-coded line segments. Figure 2 (c) shows how these line segments are split according to their x- and y-coordinates in a clockwise reading direction. In Figure 2 (d), the Saccade Plots can be seen showing the same kind of data. Figures 2 (e) and (f) illustrate variants of our visualization approach: guiding lines and curved arcs, respectively.

Since we are also interested in time and single/multiple participants, the data model for the generated matrices allows us to additionally store the needed information for time and participants.

4 Saccade Plots

This section describes Saccade Plots: a visualization technique that adds triangular adjacency matrices to the axes of a traditional heat map, allowing the viewer to inspect frequently visited fixation points or regions combined with the stimulus as well as the sequential order of visits. Figure 3 shows an example of Saccade Plots.

4.1 Triangular Matrices

As mentioned earlier, we first preprocess the spatio-temporal eye tracking data and then transform it into relational data modeling the transitions between fixations (Section 3). Relations are associated with weights or attributes to include temporal information (of the time-varying relations) or information about single/multiple participants or groups of them (male/female, age groups, etc.) in the visualization.

As new visualization technique, we introduce the concept of Saccade Plots. Such diagrams attach triangular matrices to the axes of the heat map. Each triangle expresses relations in one of four possible movement directions, i.e., west-to-east (at the top), north-to-south (to the right), east-to-west (at the bottom), and finally south-to-north (to the left). We use a clockwise reading direction here.

The single matrix entries are placed with respect to the related fixation points in the heat maps, i.e., the longer a saccade is in its

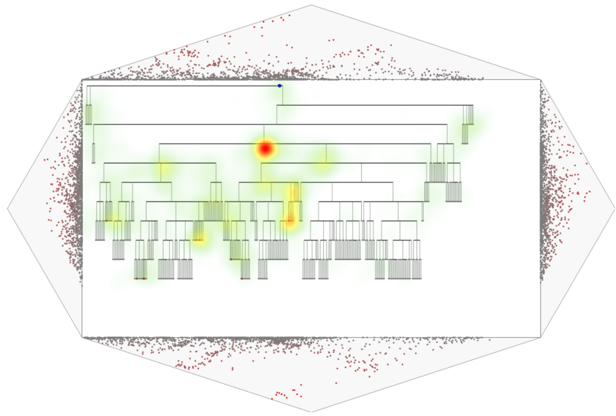

Figure 3: *A stimulus from an eye tracking study overlaid with a heat map. The attached triangular matrices show saccades with reduced visual clutter by displaying them in a matrix-based approach.*

(a) (b)

Figure 4: *Additional visual representations: (a) guiding lines and (b) curved arcs.*

corresponding x- or y-direction, the farther away the corresponding pixel is placed. This means that the longest possible saccade is mapped to a color-coded pixel (matrix entry) at the peak of the corresponding triangular matrix. The color of each matrix entry visually encodes the weight or attribute of a relation (i.e., an attribute attached to the saccade, such as participant group, time, etc.). Following this concept, we obtain a clutter-reduced visualization that is able to show all possible weighted or attributed relations in a single static view without any intersection between the visualization of saccades. Moreover, the relations are aligned with the spatial information provided by the stimulus overlaid by the heat map.

Mathematically spoken, a saccade from point $p_i := (x_i, y_i)$ to point $p_{i+1} := (x_{i+1}, y_{i+1})$ is visually mapped by

$$(p_i, p_{i+1}) \mapsto (\Delta x + \frac{(x_{i+1} + x_i)}{2}, \Delta y + \delta \cdot (x_{i+1} - x_i)) \ ,$$

where Δx and Δy are display offsets expressing the vertical and horizontal borders of the stimulus, respectively. The above equation is valid for the positive x-direction; the other directions lead to analogous mappings. $\delta \in \mathbb{R}_0^+$ is used as a stretching factor for the triangular matrix.

4.2 Visual Patterns

The Saccade Plots can be used to find insights into spatio-temporal data by inspecting visual patterns provided by the visualization. These can be described as follows:

1. **Colored regions in the heat map:** First of all, the heat map can be explored as an overview to find regions of interest, i.e., regions that are frequently visited by a group of study participants, if there are dense clusters, or if the entries are more widely spread.
2. **Distances/positions of matrix dots:** The dots in the matrices can be used to explore the lengths and start-/target positions in either x- or y-direction. This can be used to find out symmetries or asymmetries in the participants' eye movement behavior.
3. **Empty regions:** Both heat maps and matrices can contain empty regions, which indicate areas in a displayed stimulus that are of little or no interest for performing a given task.
4. **Color coding of matrix entries:** The color coding of matrix entries indicates the weight or attribute (time, participant) of the relations.
5. **Densities:** Many color-coded matrix entries in a small region express that many saccades exist between similar start and target fixation points.
6. **Overall pattern of matrix entries:** Comparing visual patterns of two opposite sides can help see whether the applied strategies differ between opposite movement directions or not.
7. **Differences between two or more Saccade Plots:** The applied visual task solution strategies can be explored for differences between displayed stimuli.

Our visualization tool also supports straight guiding lines and curved arcs—representations that show visual patterns that have to be interpreted differently, see Figure 4.

5 Case Study

We applied our visualization technique to a dataset formerly recorded in an eye tracking experiment by Burch et al. [2011], who made their data publicly available [Andrienko et al. 2012]. The study participants were shown node-link tree diagrams in different layouts and orientations where a set of leaf nodes was highlighted. The task in this eye tracking study was to locate the least common ancestor of the highlighted leaf nodes.

For our case study, we first transformed the trajectory data from this eye tracking study into our specific data formats, then visualized it, and interactively used the features integrated in our tool to explore the data with the goal to find insights that would not have been found by a heat map and a gaze plot representation separately.

We use the visual patterns described in Section 4.2 to explain our findings. We explore two different layouts of node-link tree diagrams: traditional (Figures 5 (a) and (b)) as well as orthogonal layout (Figures 5 (c) and (d)). Both of them are displayed with the root node either at the top (Figures 5 (a) and (c)) or at the bottom of the display space (Figures 5 (b) and (d)).

Section 4.2 (1) can be used to derive visual patterns from the heat maps. Here, we see some hot spots in all of the figures that refer to inner nodes and the task solution node, i.e., the least common ancestor of the marked leaf nodes in the node-link tree diagrams. This means that study participants frequently inspected these visual elements in the stimuli, which was needed to perform the given task correctly.

The lengths of the saccades can be visually analyzed by having a look at the triangular matrices as described in Section 4.2 (2). In all of the four presented figures, there are cluster structures clearly visible close to the stimuli borders, representing very short eye movements. This can be seen in all of the orientations, showing that the study participants solved the task step-by-step with (mostly) short

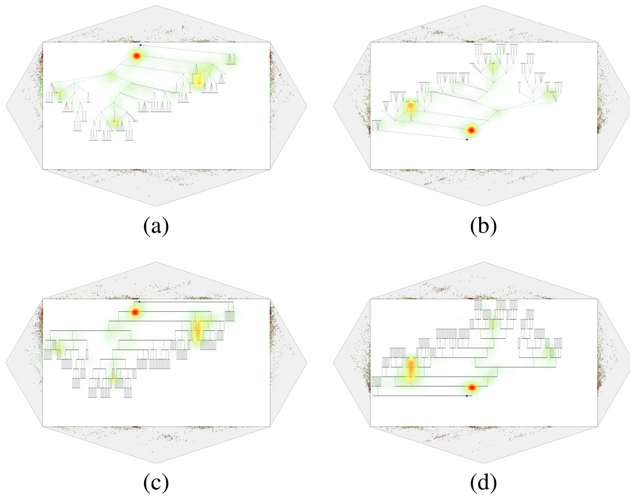

Figure 5: *Saccade Plots for stimuli that show node-link tree diagrams: Traditional layout with (a) root node at the top and (b) root node at the bottom. Orthogonal layout with (c) root node at the top and (d) root node at the bottom. All figures show the same hierarchy dataset and the same task is performed.*

eye movements and did not jump across the entire stimuli. We can find only a few outliers with very long eye movements.

Also many empty regions can be found in both the heat maps and triangular matrices. This means that either those regions are not inspected or that there are no gaze relations between two regions visually mapped to the empty regions in the adjacency matrices (Section 4.2 (3)).

The color coding in the triangular matrices visually encodes if a gaze relation occurs earlier or later in the visual exploration process (Section 4.2 (4)). A linear optimal color coding is used in all of the presented figures in the case study: darker color represents later time steps and lighter color earlier time steps. In all of the presented figures, one can see that the darker dots are aligned with the hot spot in the heat map representing the task solution node in the tree diagrams. This means that study participants finally found the correct solution that was then confirmed by a mouse click. Only a few eye movements go back to deeper hierarchy levels again.

The visual pattern explained in Section 4.2 (5) can also be found in all of the figures. Densely packed regions of color-coded dots express saccades between similar fixation points, i.e., where start and target fixation points are close to each other. For the stimuli used in the user study, this frequently happens for nodes having a special semantic meaning for solving the given task in the study.

Comparing opposite sides of the Saccade Plots shows that visual patterns are oftentimes similar. For example, inspecting Figure 5 (a), one can see this symmetry: the visual patterns for the left-to-right direction look similar to those for right-to-left movements (Section 4.2 (6)).

We can also explore the data for visual patterns in different stimuli representing the same dataset (Section 4.2 (7)). For the stimuli in Figure 5, we see that the visual patterns for traditional and orthogonal diagrams look similar if the orientation is the same. If the orientation is switched from top-to-bottom to bottom-to-top, the visual patterns are mirrored in a similar way.

6 Conclusion and Future Work

We have introduced a combination of heat maps with an adapted version of adjacency matrices in order to give an overview of eye movement data. Our Saccade Plots allow us to understand more than the time- and participant-aggregated data in traditional heat maps or cluttered gaze plots, as demonstrated in our case study. An additional benefit of Saccade Plots is the clutter-free representation in triangular matrices.

However, our visualization also comes with some disadvantages: First, the temporal order of the saccades is generally lost in the Saccade Plots, i.e., only clusters of saccades, their lengths, and start/target positions can be explored in an overview representation. The temporal information is only obtained by applying a color map encoding the time dimension. Second, additional ambiguities might be introduced by splitting saccades into x- and y-components. A visual recombination of this information cannot be achieved since there is no visible relation between the x- and y-components.

In future work, we plan to consider dynamic stimuli such as movies or interactive graphical interfaces; here, the data analysis becomes more challenging because there is no static stimulus to which matrices could be attached.

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