Color Bands: Visualizing Dynamic Eye Movement Patterns

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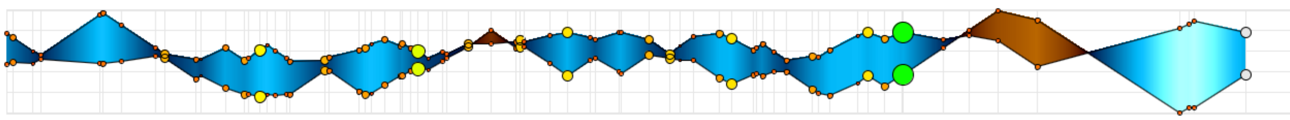

Figure 1: A color band showing the time-varying eye movement patterns of an individual participant (time along the horizontal axis): x- and y-coordinates of gaze data as well as their differences can be visually inspected by observing the vertical positions, thickness, and color of the band.

ABSTRACT

We introduce a visualization technique called color bands for showing the time-varying eye movement behavior of eye-tracked people. Our contribution is the clutter-free representation of time-varying x- and y-positions of gaze data. We map these coordinates to vertical positions from left to right as in traditional line plots. On top, we display the differences between the x- and y-coordinates by the thickness of the band. Fixation durations are visually encoded as circles of varying diameters. Color coding is used to additionally enhance the distance values and the durations in order to perceptually benefit from pattern recognition for an individual participant but also to compare the eye movement behavior of several participants. We illustrate the usefulness of our technique in a case study investigating eye movements from a formerly conducted eye tracking study on the readability of node-link tree diagrams.

Index Terms: H.5.2 [Information Interfaces and Presentation]: User Interfaces—Graphical user interfaces (GUI);

1 INTRODUCTION

This paper addresses a problem of visual data analysis of eye tracking data acquired for individual participants and groups of participants alike. It is difficult to fully analyze and understand all facets of such spatio-temporal data, especially for long eye movement trajectories and large numbers of participants. Many existing visualization concepts aggregate over participants and over time like visual attention maps [3, 16] or they show the time-varying behavior of many people as color-coded polylines plotted on top of each other [1, 15], producing visual clutter [14]. Both concepts—referred to as heat maps or gaze plots—are common visual representations of eye tracking data; however, they either show only half of the truth or do not visually and perceptually scale to large eye movement datasets.

In this paper, we argue that a clutter-free static visualization can have many benefits for getting an overview of the time-varying visual attention of several participants taking part in eye tracking studies. To reach this goal we introduce *color bands*: they encode time along the horizontal axis (in left-to-right reading direction), saccade lengths are proportionally mapped to x-axis sections, saccade orientations to vertical gradients, the x- and y-positions of gazes to vertical positions, and the differences between x- and y-coordinate values to vertical distances and color. The distances between two consecutive fixations are indicated by the changes of the band shape over time, whereas the fixation durations are encoded as circles of different sizes placed at the end of each polyline segment, see Figure 1. This visual mapping allows us to explore the visual attention of several participants in parallel, avoiding any aggregation or overplotting. Moreover, it results in aesthetically appealing diagrams.

We illustrate the usefulness of our novel visualization technique for the example of eye movement data from a formerly conducted eye tracking study [5, 6]. We identify static and dynamic visual patterns, but also patterns of individual participants and groups of them, and finally, have a look at scalability issues concerning algorithmic, visual, and perceptual aspects.

2 RELATED WORK

There are several visualization techniques dealing with eye movement data, as surveyed by Blascheck et al. [2]. Most of them aggregate eye movement data over space, time, or participants. For example, heat maps or visual attention maps [3, 4, 16] show a condensed view of the visual attention of a group of participants aggregated over a certain time period. Only the hot spots of visual attention are visible by visually inspecting the color-coded hot spots in a corresponding diagram. In contrast, gaze plots [1, 15] do not aggregate over time nor over participants, but overplotting of many polylines leads to visual clutter [14], "a state in which excess items or their disorganization leads to a degradation of performance at some task."

AOI rivers [7] show the time-varying behavior of many eye tracking study participants, but they aggregate over all participants, making it impossible to identify similar strategies of certain people over longer time periods. This Sankey-based [17] diagram style merges and splits, i.e., single trajectories cannot be traced. The approach is based on the ThemeRiver visualization [9], which uses vertically stacked bands to indicate the number of visits to Areas of Interest (AOIs) over time. We do not specifically focus on AOIs nor do we vertically stack the color bands in our color bands visualization. Our approach is more related to the CloudLines technique [10] using non-stacked, but horizontally time-aligned rivers, which helps better visualize value changes [8] over time and visually compare them with the others.

Approaches like parallel scanpaths [13] are other visualization techniques that somewhat resemble our work, but they require the definition of AOIs and lack the visual representation by color bands. We have also added visual features for the fixation duration and ad-

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ditionally encoded value changes between the x- and y-coordinates.

Gaze stripes [12] work well for additionally showing snippets of the displayed stimulus, but the technique fails to support an analyst in seeing correlations among the time-varying coordinate behavior if the stimulus contains similar subregions and subfeatures. Moreover, it becomes hard to identify common visual task solution strategies among a large group of participants. Similar problems occur in fixation image stripes [11], in which additional statistical data on the eye movement behavior is given.

3 Data Model

In this paper, we deal with eye movement data recorded from several participants. These can be modeled as a set of $n \in \mathbb{N}$ individual spatio-temporal trajectories (scanpaths)

$$S := \{S_1, \ldots, S_n\}.$$

These trajectories model sequences of fixations:

$$S_i := (p_{i,1}, \ldots, p_{i,m_i}),\ 1 \leq i \leq n.$$

Each individual fixation point $p_{i,j}$, $1 \leq j \leq m_i$ is typically associated with a duration value $t_{d_{i,j}}$ acting as the time span that reflects the point in time the eye enters a fixation $p_{i,j}$ and the point in time it leaves it again. The movement of the eye from one fixation point to a subsequent one is referred to as a saccade—a rapid movement of the eye where no visual attention is paid. For our technique to work reliably, we need such saccade information, which can be extracted from the sequence of fixation points. Those finally result in the characteristic time-varying visual patterns that we need for exploring the eye movement data.

4 Color Bands Visualization

We provide a simple visualization technique with which time-varying eye movements in a 2D static scene can be displayed without visual clutter. Moreover, the eye movement data is neither aggregated over time nor over participants. Therefore, the visualization serves as an overview representation for visually exploring dynamic eye movement patterns. These patterns can be explored for individual eye-tracked people but also for groups of them on a comparative basis.

4.1 Visual Design for Single Band

Figures 2, 3, and 4 illustrate the general concept of the color band visualization. The distances between x- and y-coordinate values are visually enhanced by color coding that builds another visual feature apart from band thickness, making the visualization perceptually more effective [18]. The fixation durations are given by circles of different sizes. These can be visually and perceptually enhanced by additional color coding.

In particular, the data variables are visually encoded as follows:

- **Time dimension:** The time is mapped along the horizontal axis, starting with the earlier points in time at the left-hand side and progressing to the right-hand side as time passes by. This follows a left-to-right reading direction.
- **Fixations/durations:** Fixations to points of interest (POIs) are visually encoded as circles of varying sizes depending on the fixation duration. The circle size is displayed in relation to the longest fixation duration in all of the eye movement trajectories. Color coding is additionally used to support analysts in comparing fixation durations. Each circle is placed at the horizontal position where two saccades are linked.
- **Saccades:** Each saccade is given by a start and an end point in 2D space. The x- and y-coordinates are split into two separate lines while all x-coordinates in a sequence are linked and also the y-coordinates, respectively. This results in a time-varying visual model of the sequence of saccades. The vertical placement of the coordinates is useful to visually explore the dynamic changes among the coordinates and hence, the eye movement trajectory in 2D space. Color coding is used to perceptually increase the coordinate differences.
- **Saccade length:** The length of each saccade (the Euclidean distance between start and end point in 2D) is proportionally mapped to the horizontal axis. This is useful to visually explore the varying saccade lengths over time.
- **Differences between x- and y-coordinates:** The differences between the coordinates are visually encoded by varying thickness of the band and perceptually enhanced by color coding. This supports static and dynamic pattern recognition. Moreover, a bipolar (diverging) color coding is useful to see whether the x- or y-coordinate values are larger.
- **Space/stimulus:** The spatial dimension is represented by the x- and y-coordinates. This means that the stimulus is not explicitly given in a visual form, but the sequence of positions can be taken into account to get an overview of the approximate visually attended regions in the stimulus.

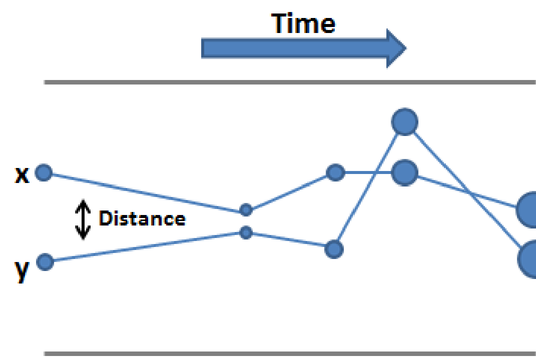

Figure 2: The time-dependent x- and y-coordinates of gaze data for one study participant are visually represented by polylines similar to line charts. Time is mapped in a left-to-right reading direction. The saccade lengths are proportionally encoded in the horizontal lengths. The fixation durations are displayed as circles of different sizes.

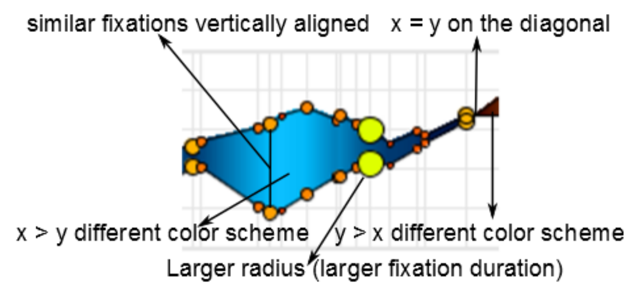

Figure 3: A part of a color band with descriptive visual features used to highlight time-varying eye movement patterns.

4.2 Visual Design for a Sequence of Bands

We map a set of eye movement trajectories (either from many study participants for the same stimulus or for one participant having inspected several stimuli) to the vertical axis. The stacking and alignment of the color bands supports comparison tasks that help identify

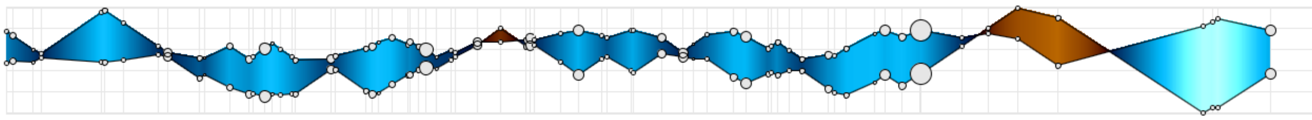

Figure 4: Showing a color band for an individual eye tracking study participant. The displayed stimulus was a node-link tree diagram with the root node placed to the left-hand side. To answer the study task the participant did 70 fixations with differently long fixation durations. The x-coordinate values are mostly higher than the corresponding y-coordinate values while the saccade lengths are changing frequently.

commonalities or differences among several of those color bands and hence, explore the time-varying eye movement behavior of eye tracking study data.

The eye movement trajectories can be aligned in several ways:

- **Longest saccade length sum:** The maximal sum of all saccade lengths can be computed while each saccade in the sequence is horizontally mapped proportionally to this maximal sum. This results in color bands of different lengths, but positively, the trajectories are comparable based on the saccade lengths.
- **Normalized saccade length sum:** All of the color bands can be stretched, making them all equally long. This effect can be useful to understand the time-varying behavior if all participants have to end with their task at the same position in the stimulus (the task solution).
- **Sum of fixation durations:** Instead of taking space or distances for the horizontal lengths of the color bands, also the time duration can be taken into account. This can give additional insight into the distribution and sum of fixation durations, although these are already mapped to circle sizes and color.

4.3 Meaning of Visual Patterns

With our color band visualization, we can easily identify visual patterns that can be remapped to the eye movement data in order to explore and analyze it. There are several visual patterns that might occur depending on the dataset scenario under exploration like static or dynamic patterns or those concerning individuals or groups of people.

- **Static/dynamic patterns:** Visually inspecting an individual color band provides information about points in time, but also longer time periods might be worth investigating.
  - **Saccade length behavior:** The frequencies and lengths of the saccades can be explored by either looking at the changing band patterns or additionally taking into account the fixation patterns, but also the vertical gray lines.
  - **Position on top/bottom/center:** The positions of the band lines describe which x- and y-positions in the stimulus are visually attended. The closer to the top these are placed, the lower are the corresponding values.
  - **Thick/thin bands:** The thickness of each band expresses the difference between the values. The thicker the band is, the larger is the distance. If the lines are placed on top of each other, x- and y-values are the same, i.e., a value on the diagonal is fixated.
  - **Crossing/parallel pattern:** Parallel lines indicate that the x- and y-values have the same change behavior. A crossing pattern shows that a formerly larger value has become smaller than the other one.
  - **Increase/decrease of coordinate values:** The degree of increase or decrease of values can be inspected by the gradient of the individual lines.
  - **Alternating/oscillating behavior:** Alternating behavior can be visually explored by inspecting the periods of changes of the dynamic pattern, i.e., growing and shrinking behavior of the 'dents'.
- **Individual/group of people:** An individual color band can be visually explored for static or dynamic patterns but also more of them might be of interest, in particular for comparison tasks of visual task solution strategies.
  - **Similar/dissimilar visual attention behavior:** Comparing different color bands supports the detection of similar or different visual task solution strategies among participants or even participant groups. In the simplest scenario, an individual participant can be analyzed for his/her behavior.
  - **Velocity of people:** Having color bands placed next to each other helps understand the different answering velocities of eye tracking study participants.
  - **Time-shifted strategies:** Since the visualized data has a time-varying nature, we might also be interested in detecting dynamic patterns that occur for several study participants in the same or similar way but that are temporally shifted. This means that someone might have found the correct strategy much earlier or later than others.
  - **Outlier participant:** If a strange eye movement behavior occurs not matching all the others, we speak of an outlier or anomaly.

These are the most important visible patterns, but there are many more like also the combination of several of those patterns.

5 Case Study

We take a closer look at the eye movement data from an earlier controlled user study that investigated the readability of node-link tree diagrams [5, 6]. The eye movement data is publicly available. It contains the eye movements of 38 participants all having visually inspected more than 50 static 2D node-link tree diagram stimuli. As a simple application scenario, we take one specific node-link tree diagram where the root node is placed to the left, three leaf nodes are highlighted, and a traditional layout is applied. We are interested in the visual attention behavior of the participants.

We first preprocess the time-varying data for our tool-specific data format consisting of saccadic information and fixation durations. Then for each participant, a color band visualization can be shown while all of them are horizontally aligned and stacked on top of each other, supporting the detection of similar visual task solution strategies (see Figure 5).

As we can see from Figure 5, there are 10 eye movement patterns under observation. All participants had to visually inspect a node-link tree diagram while finding the least common ancestor of

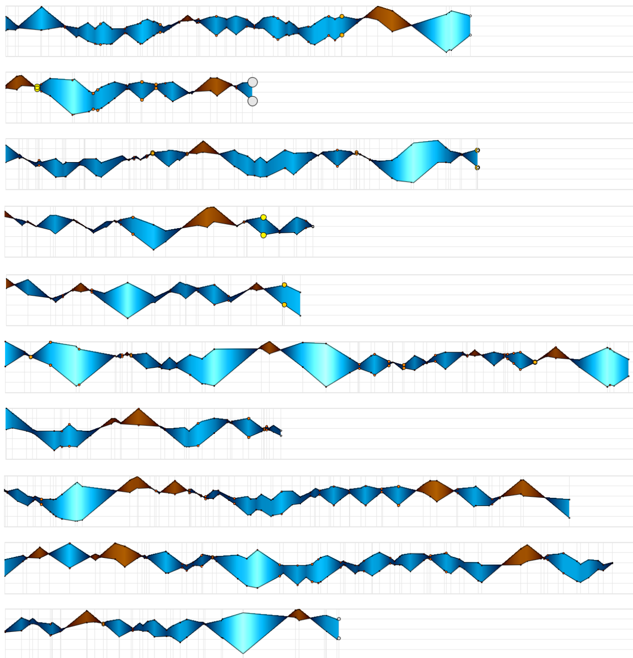

Figure 5: A group of eye tracking study participants inspecting a stimulus from a node-link tree diagram study [5, 6]. The individual eye movement patterns are visualized as color band visualization using a bipolar color coding that shows whether the x- or the y-values are larger. The stacking of the bands reflects the common substrategies and also the differences among them.

a set of highlighted leaf nodes. Therefore, the participants ended up more or less at the same position in the static stimulus.

For the visualization, we used a horizontal alignment given by the sum of saccade lengths. The color coding uses a white-to-blue color scheme for the case when x-values are higher, and a heated object color scheme for the case when the y-values are higher. These blueish and brownish colors help us perceptually separate the time spans where x- or y-values are more dominant, respectively.

We can directly see from the figure that the overall visual task solution strategy is rather similar apart from several participant-characteristic visual features. For example, participants 6, 8, and 9 have a larger sum of saccade lengths, which can be seen by the color bands heading farther toward the right-hand side. The overall color coding is a blue one, indicating that over time mostly the x-values are larger than the corresponding y-values. This reflects that the participants rather visually inspect the upper right part of the stimulus. We can also see that the differences between x- and y-values do not differ that much over time. Only a few 'dents' indicate that in some situations they are really different. Most of the participants visually scan regions with lower x-coordinate values and this scenario also happens more toward the end, which is close to finding the correct target node and answering the task correctly.

The saccade frequencies are pretty high for some participants, reflecting that people rather looked in short spatial distances to solve the given task. Only the people's behavior corresponding to color bands 6, 8, and 9 reflects that longer jumps have been done to answer the task. The fixation durations are pretty low and more or less equally distributed, which can be seen by the color-coded circles. This means that people do not visually attend specific points for a long time while inspecting the diagrams, which is again a hint that the intermediate steps to answer the task did not show up as problematic aspects.

6 Limitations and Scalability

Although our technique is able to show the time-varying visual scanning behavior of a list of eye tracking study participants, there are several limitations. These can be distinguished by algorithmic, visual, and perceptual aspects.

- **Algorithmic scalability:** The general transformation of an eye movement trajectory into a corresponding color band is not computationally complex, but once we start adding clustering, filtering, and automatic pattern detection and comparison techniques, the required algorithms can be rather time-consuming, hence, having a bad impact on interactivity.
- **Visual scalability:** Since we use a time-to-space mapping for a sequence of eye movements, we will reach space limitation issues in the horizontal direction once the sequences become rather long. Also the number of eye tracking study participants has an influence on the vertical display space for an individual color band. To solve this issue, filtering interactions should be provided.
- **Perceptual scalability:** Since we are dealing with additional color coding to make the color band visualization more perceptually efficient and to benefit from an aesthetical appearance, we may have problems concerning the choices of adequate color scales.

7 Conclusion and Future Work

We have introduced a visualization technique for showing time-varying eye movement patterns. The approach has the benefit that visual clutter is reduced compared to traditional gaze plots and that the eye movement is not shown in an aggregated fashion like in visual attention maps—neither aggregated over time nor over study participants. An advantage of the color band visualization is that we can still recognize time-dependent eye movement patterns while comparing them between the individual eye tracking study participants. To reach this goal we make use of several visual variables—band thickness/circle size and band and circle color—a visual mapping that exploits the strengths of the human visual system for rapid pattern detection.

For future work, we plan to extend the technique with automatic dynamic feature detection and clustering approaches for grouping similar eye movement behaviors. Moreover, a user evaluation is required to assess if users will perform better with this novel technique, for example, compared to standard techniques like visual attention maps, gaze plots, or parallel scanpaths.

Acknowledgements

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