Visually Comparing Eye Movements over Space and Time

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ABSTRACT

Analyzing and visualizing eye movement data can provide useful insights into the connectivities and linkings of points and areas of interest (POIs and AOIs). Those typically time-varying relations can give hints about applied visual scanning strategies by either individual or many eye tracked people. However, the challenging issue with this kind of data is its spatio-temporal nature requiring a good visual encoding in order to first, achieve a scalable overview-based diagram, and second, to derive static or dynamic patterns that might correspond to certain comparable visual scanning strategies. To reliably identify the dynamic strategies we describe a visualization technique that generates a more linear representation of the spatio-temporal scan paths. This is achieved by applying different visual encodings of the spatial dimensions that typically build a limitation for an eye movement data visualization causing visual clutter effects, overdraw, and occlusions while the temporal dimension is depicted as a linear time axis. The presented interactive visualization concept is composed of three linked views depicting spatial, metrics-related, as well as distance-based aspects over time.

CCS CONCEPTS

• **Human-centered computing → Visualization techniques**;

KEYWORDS

Eye tracking, information visualization, visual analytics

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1 INTRODUCTION

There is a growing interest in the field of eye tracking [Duchowski 2003; Holmqvist et al. 2011], since with this emerging technology, researchers in visualization (but also in many other application domains like marketing, psychology, text reading, or human-computer interaction) can get hints about the visual attention and scanning strategies of human inspectors while they use a diagram or a visual depiction of data [Kurzhals et al. 2017, 2014]. Although tracking people's eyes has become much easier these days, due to the progress in hardware technology, the analysis of the data has become a challenging problem - algorithmically as well as visually [Blascheck et al. 2015; Kumar et al. 2018].

Major reasons for this issue are the growing amounts of data, a trend that also takes place in the field of eye tracking [Blascheck et al. 2015]. Such spatio-temporal data attached by additional physiological data and derived metrics can be produced at ever increasing rates due to the more exact and faster becoming tracking technologies. Not only the increasing amount of the data plays a crucial role for data analysis, but also the inherent nature of the data itself which is a spatio-temporal one.

The spatial dimension makes a comparison between scanpaths of various people difficult, even impossible. The reason is the displayed stimulus that serves as contextual information in order to set the scanning strategies in context to the semantics of the visual aspects [Yarbus 1967]. Finding a good visual metaphor that supports scanpath comparisons over space and time simultaneously is a challenging task. Reflecting both data dimensions in a single view is pretty difficult since the visual stimulus with its spatial dimension typically restricts each visual metaphor with the stimulus-in-focus. But designing a diagram for aligning the data in the visualization over time while also depicting the spatial information to some extent is a suitable concept.

There exist already various visualization techniques for eye tracking data as surveyed by Blascheck et al. [Blascheck et al. 2017] but most of them either suffer from visual clutter [Rosenholtz et al. 2005] or they aggregate time and participants, meaning time-varying behaviors cannot be easily explored. Moreover, additional metrics like saccade lengths and orientations or fixation durations cannot be rapidly recognized by the human analyst. On top of this, most of the existing visualization techniques do not support the visual encoding of time-dependent distances between points or areas of interest. Hence, a combination of these aspects is important to identify phases in the visual scanning behavior of eye tracking study participants.

In this paper we introduce a linked visualization [Roberts 2004] that combines spatial, metrics-related, and distance-based aspects with the goal to visually compare visual attention behavior over space and time. This combination provides a way to explore scanpath data from different perspectives. The visualization is supported by interactive concepts for detecting similarities and dissimilarities between the scanning strategies of several eye tracking study participants, but also between different stimuli, for example, by investigating an individual study participant. To reach the visualization goal, we provide three different timeline-based views: color bands, metrics timeline, and distance arcs. These views are temporally aligned making it easier to identify phases based on several

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aspects and not on one as in most existing approaches. We also provide a direct linking to the stimulus, i.e., to show the spatial dimension for extra contextual information.

2 RELATED WORK

Blascheck et al. [Blascheck et al. 2017] surveyed the state-of-the-art for eye tracking and visualization and found many techniques focusing on the visual depiction of this kind of data. Inspecting all of the discussed techniques reveals that most of them more or less provide a visual representation for a specific aspect in the data. For example, heat maps [Bojko 2009; Spakov and Miniotas 2007] show a scalar density field for the visual attention of one or more study participants. By doing this, spatial information is provided, but temporal aspects or metric-based aspects are completely invisible. Fixation distances are provided in a natural way due to the direct observation of the spatial environment, but also time-varying behavior of the fixation distances cannot be observed. Moreover, it is impossible to derive dynamic scanning strategies purely based on the density fields. Comparing individual participants might be possible by small multiples [Tufte 1992] of visual attention maps. But due to the 2D nature of the maps, the visual comparison has to be done over two dimensions which we try to improve by generating a more linear time representation that requires to find further visual variables for the spatial dimension of the stimuli.

Burch designed the time-preserving visual attention maps [Burch 2016], but although time is visually encoded, it is impossible to judge distances over time nor is it possible to see metrics like saccade lengths or orientations and fixation durations at the same time. Moreover, comparing several participants is only possible by applying interaction techniques, but an individual overview-based diagram cannot be provided to support such visual scanning strategy comparisons. In general, visual attention maps are based on fixation aggregations and typically, only provide an overview about more or less frequently visually attended regions, those are neither designed for comparing dynamic visual attention strategies nor for supporting comparison tasks between participant strategies.

Andrienko et al. [Andrienko et al. 2012] survey visual analytics methodologies for eye movement studies. In their work, also some visualization techniques are described that focus on the time-dependent scanning behavior. They also discuss small multiples of visual attention diagrams that are mostly plotted on top of a visual stimulus, but although time can be inspected, it is pretty hard to judge distances while at the same time bringing metrics in correlation to all of the other aspects. The general drawback of most of those small multiples approaches comes from the comparison that has to be done by inspecting horizontal and vertical directions. A more line-based representation that makes use of color coding the individual scan paths while those are depicted as horizontally stacked timeline diagrams [Burch et al. 2013a], provides an overview, but distances and metrics cannot be derived easily. This color coding is similar to the color bands technique [Burch et al. 2016], but in the color bands, the different polygonal shapes additionally perceptually support the identification of scanning similarities and dissimilarities.

Gaze plots [Goldberg and Helfman 2010] are a useful approach integrated in most eye tracking systems. Those belong to the most traditional approaches to represent eye movement data, but although the time-dependent visual attention is shown it becomes pretty hard to explore the data for the dynamics of applied visual scanning strategies. The overdrawing, occlusion, and visual clutter [Rosenholtz et al. 2005] effects are to blame for the degradation of performance at such dynamic pattern identification tasks. For this reason, Raschke et al. [Raschke et al. 2012] solved this problem by visually encoding the data as parallel scanpaths. This means they investigate a more linear representation of the spatio-temporal data by splitting x- and y-coordinates and represent them on separate linear axes. Although their approach is comparable to our novel idea, Raschke et al. do not consider data aspects like spatial information or fixation distances over time. Moreover, it is difficult to relate the x- and y-values since those are not visually encoded by extra visual variables like in the color bands approach.

Typical line-based representations for eye movement data do not allow to see combined views of several aspects in the data like space, metrics, and distances between fixations. For example, the AOI rivers [Burch et al. 2013b] focus on the aggregated visual attention over time while also showing the transitions between areas of interest. On the negative side, it is not possible to see if participants went back over time while still exploring the fixation durations and saccade lengths for example. Blascheck et al. [Blascheck et al. 2016] research the idea of building a hierarchy of fixation sequences, but although hierarchical clusters might be detectable, an analyst cannot easily see time-varying patterns and phases, nor are fixation distances and dynamic spatial information included. The gaze stripes [Kurzhals et al. 2016b] by Kurzhals et al. include image thumbnails from the stimulus to give the analyst a way to explore the semantic information in order to give hints about the locations people are visually attending. But if a stimulus consists of many similar textures and objects (like a checkerboard) such thumbnails become useless for identifying spatial behavior. In our approach we are not restricted to the stimulus semantics. Similar problems occur in the fixation image charts by Kurzhals et al. [Kurzhals et al. 2016a] although additional metrics-based information is provided.

Burch et al. [Burch et al. 2016] designed the color bands technique which is useful to find a more linear approach making it possible to map the eye movement data to a 1D time axis while still seeing the time-varying visual attention patterns. Color coding is used to reflect the connectedness of the x- and y-values. We got inspired by this idea, but missed additional data aspects like fixation distances that are also described in another work by Burch [Burch 2017b]. Also Kasprowski and Harezlak [Kasprowski and Harezlak 2017] encoded distances as self-similarity plots in a matrix-like scheme, but additional views on the scanpath data are not provided simultaneously.

Graphs might be computed from the spatial relations but by abstracting to graph data and visualizing that, the spatial information as well as the distances are lost [Burch 2017a]. If the focus is more on fixation distances, those can be directly attached to the timeline-based diagram like in the work by Wattenberg [Wattenberg 2002] using curved links, i.e., arc diagrams.

A more combined and linked representation of several aspects inherent in eye movement data can be beneficial. To reach this goal, the time axis should be displayed in a more linear way [Aigner et al. 2011], i.e., like plotting it in a left-to-right reading direction.

3 EYE MOVEMENT DATA

In this paper we focus on eye movement data, i.e., the spatio-temporal but also metrics- and distance-based aspects. All of the data components can have a time-dependent component that is important for the algorithmic as well as visual concepts in this work. We first briefly describe eye movement data in form of scanpaths and then look into data transformations like mappings from 2D to 1D to get a suitable approach for aligning the different views. Then we have a look into eye tracking metrics and fixation distances. In particular, the mapping from 2D to 1D supports the better alignment of the data to a linear timeline, a way to allow visual comparisons over time.

3.1 Scanpaths

Eye movement data for one study participant can be regarded as a trajectory consisting of a sequence of points, i.e., a scanpath [Noton and Stark 1971]. The points are referred to as the fixations while the movement of the eyes from one point to the next one are denoted by the term saccade. It is said that semantic information is typically acquired during the fixations and not during the saccades. But on the other hand, saccades are important in a visualization since they can tell us where the eyes have moved, i.e., in what direction and over what distance.

Fixations can have a duration while the saccades typically have a length and an orientation. Those aspects about the data are important to visually encode in combination since they provide an easy way to get first impressions about the eye movement data [Holmqvist et al. 2011]. For example, it is said that the longer one fixates a point on a stimulus, the more problematic it might be to understand the semantics of the displayed stimulus at this location [Scinto et al. 1986]. If the saccades are longer, typically, the participants are able to understand and read the stimulus. The insights from the time-varying behavior of these trivial metrics can already give a hint about phases, i.e., the dynamics, in the visual scanning strategies but should be complemented by additional views.

A scanpath can mathematically be modeled as

$$S := (p_1, \ldots, p_n)$$

while the p_i's describe the fixation points, i.e., they carry the spatial information of the stimulus and $n \in \mathbb{N}$ expresses the number of fixation points in the scanpath. Each p_i is additionally attached by a fixation duration, i.e., a quantitative value. The saccade and distance information can be derived easily from the point sequence and later be used for providing additional views on the scanpath data. If we have to deal with several study participants, i.e., several scanpaths we denote them by

$$S_i := (p_{i,1}, \ldots, p_{i,n_i}).$$

It may be noted that scanpaths can be of different length depending on the number of fixation points measured by the eye tracking device. This effect is expressed in the number $n_i \in \mathbb{N}$.

Representing all of the aforementioned aspects of eye movement data in a single visualization is a challenging task and as described in the related work section, all of the existing approaches can either only show a few aspects or they are not useful for visual scanning strategies among study participants or different stimuli for the same participant. In our approach we try to combine the benefits of several techniques in a time-aligned way in order to better temporally compare the applied scanning strategies. For this reason the scanpaths have to be transformed into a more linear representation, hence going away from the traditional spatial restriction given by a visual stimulus.

3.2 Transforming the Space

To achieve a useful representation of the eye movement data it is important to transform the 2D fixation points to 1D positions along a time axis. The transformation from 2D to 1D supports the better alignment of the data to a linear timeline, a way to allow visual comparisons over time [Burch 2017b; Burch et al. 2016]. This is important to provide a representation that is freed from visual clutter, overdraw, and occlusion effects that occur when it is restricted to the spatial information of the stimulus. At the same time, space and time should be observable data dimensions in the corresponding visualizations.

To reach this goal, we separate each point $p_i := (x_i, y_i)$ into its x- and y-components and use the time information given by the eye tracker (typically the sum of fixation durations) to build the new mapping. This new mapping is then freed from the visual stimulus since it flattens the eye movement trajectories which has benefits for our novel visualization, but also brings new drawbacks into play if someone is more interested in semantic information from the stimulus. The linearly transformed scanpaths build the basis for attaching several other eye tracking metrics as well as distance plots making it possible to compare the visual scanning strategies of several study participants.

Each two-dimensional point $p_i \in \mathbb{N} \times \mathbb{N}$ now becomes a pair of pairs expressing two new vertically stacked points with $(t_i, x_i) \in \mathbb{N} \times \mathbb{N}$ and $(t_i, y_i) \in \mathbb{N} \times \mathbb{N}$ where t_i just expresses the time point at which the fixation happened and x_i and y_i are the coordinates for the vertical positions of the new transformed points. This transformation of 2D spatial data is important for the color bands view and has also been described in the work by Burch [Burch et al. 2016].

4 EYE MOVEMENT DATA VISUALIZATION

Typically, a visualization or visual analytics approach for eye movement data describes an individual technique for displaying one or more data aspects. On the other hand, it might be composed of several stand-alone views that are sometimes linked by interaction techniques providing highlights between the views. In our work we try to combine several aspects inherent in eye movement data into a single visually aligned representation while it is supported by algorithmic concepts and interactions. However, understanding the pattern of searching for different users is not an easy task using the presented visualization, specially when analyzing the orientations, direction, and the linkage of different AOIs in different parts of an image or multiple images. For this reason we also support several interaction techniques.

4.1 Design Decisions for Problematic Scenarios

The goal of this work is to find a suitable representation for eye movement data that is not perceptually limited by spatial restrictions given by the stimulus. Moreover, we focus on time-varying fixation patterns and comparisons between them over space and time, but also based on typical eye tracking metrics and fixation distances. Our visualization is suitable for typical scenarios for which most of the existing techniques (like gaze plots or visual attention maps) would fail for such dynamic comparison tasks.

- **Scenario 1 (SO1) - Small regions:** If only small stimulus regions are visually attended, typical visualization techniques cannot be used because the differences over time are too small.
- **Scenario 2 (SO2) - Jumping:** If the eyes jump back and forth many times, for example in a cross checking behavior, most of the existing techniques are not able to visually depict such scenarios.
- **Scenario 3 (SO3) - Leaving display:** In some eye tracking situations the eyes might leave the stimulus or even the display on which it is placed. Existing techniques with the stimulus in focus cannot show such phenomena.
- **Scenario 4 (SO4) - Oscillations/trends:** If there are many similar visual scanning strategies over time like an oscillating behavior or metric value trends, this is difficult to be shown by traditional eye movement visualizations.
- **Scenario 5 (SO5) - Fixation distances:** In stimulus-based visualizations we have to judge the time-varying fixation distances. This is perceptually problematic if the scanpaths are overdrawn or not shown at all. In particular if there are many similarly long ones, this task is hard to solve.

Moreover, for all of those scenarios, it is difficult with existing techniques to compare several study participants' visual scanning strategies. Hence, our novel approach has some benefits.

From a visualization and visual perception perspective, we designed this technique with several goals in mind.

- **Occlusion/overdraw:** Typical visualizations with the stimulus in focus suffer from occlusions and overdraw of the scanpath data with the stimulus. This situation demands for extra interaction techniques to see both the scanpath and the semantics of the stimulus at the same time.
- **Visual clutter:** Long scanpaths, typical for long-durating tasks, cause visual clutter effects, in particular if those occur in similar small regions of the stimulus. Moreover, if several study participants are eye tracked, the clutter effect becomes even worse, hence comparison tasks over space and time can hardly be solved.
- **Stimulus semantics:** The semantics of the stimulus, i.e., the visual content plays a crucial role for stimulus-in-focus visualization techniques. If there are many similar textures or objects like in a checkerboard, comparison tasks become problematic if those are not supported by additional views on the data.

4.2 Color Bands

The first view (on top) is important to get an impression about the time-varying behavior of visual attention over space. To have a visually scalable uncluttered representation we first transform the 2D point sequence caused by the two-dimensional stimulus into two 1D sequences (as described in Section 3.2). The 1D property of the data allows a mapping to a timeline while the connectedness

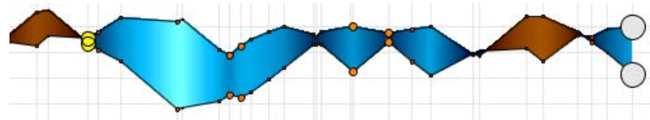


Figure 1: A color band for a short scanpath. The color coding additionally helps to judge the differences between x- and y-values. Blue and brown color codings indicate if the x- or the y-coordinate is higher.

of the x- and y-coordinates is still obtained by their horizontal alignment and by applying color codings to the enclosed areas, i.e., the color bands. The time axis is oriented from left to right while the vertical axis in the color bands view is used to depict the x- and y-coordinates. We are starting with small values to the bottom and large values are on the top. The color coding follows a user-defined color scheme and each difference between x- and y-values is assigned a specific well-defined color. It may be noted that also negative values can occur, hence we recommend to use bipolar color schemes.

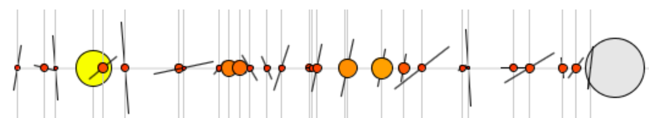


Figure 2: A metrics timeline is useful to visually explore the fixation durations as well as saccade lengths and orientations over time.

The individual 1D sequences are linked by straight lines (also done in trajectory visualizations to indicate the sequential order among the points). To further benefit from perceptual strengths and to make the color bands more aesthetically appealing, color coding is used as an extra visual variable to illustrate the value distances between x- and y-coordinates. Moreover, if x- and y-coordinates swap their vertical positions, a different color scale is used. This additionally helps the viewer to identify strong differences in the visual scanning behavior over space.

Figure 1 illustrates a color band for a scanpath consisting of a few fixation points. We can see that there are two brown color coded shapes indicating that the x- and y-coordinates changed by their difference, i.e., x is now larger than y. This is useful to see in which triangular part someone is doing fixations at the moment, i.e., above or below the diagonal. From the color band we can also see the size of the difference between x- and y-values, either by the color coding or by judging the vertical distances. If the border lines of the bands are nearly horizontally arranged and running in parallel, this is an indication that someone is fixating the same or similar point in space. Such a scenario (SO1) can hardly be detected by traditional visualizations like gaze plots or visual attention maps. We also added a fixation duration information by color coded circles of varying sizes. The larger a circle, the longer someone fixated on this point. The circles additionally help to see the frequency of fixations, i.e., if many of them occurred in a short time period or if in the same time only a few longer fixations have been done. Those are also integrated into the metrics view.

The color bands technique is typically suited for problematic scenarios like those described in SO1 to SO4. Fixation sequences in small regions can be detected by small changes in the color bands (SO1). If the eyes jump a lot over the stimulus, the color bands change the color coding and the shapes very frequently (SO2). A leaving of the display or the stimulus can be visually reflected in the color bands. Negative axis numbers can be used to show this scenario while the color coding can indicate such a situation (SO3). Oscillating behavior can be detected by periodically repeating color and shape patterns (SO4). Pairwise fixation distances cannot be judged by the color bands technique (SO5).

Figure 3: Distance arcs are useful to get an impression about the pairwise distances of fixations over time. Color coding is applied to show the strengths of the distance values. Interaction techniques can be used to filter the otherwise crowded and cluttered distance arcs.

4.3 Metrics Timeline

The center view shows the metrics timeline. Here, additional data aspects like fixation durations, saccade lengths or saccade orientations are depicted. This visualization is important to get an overview about the time-varying behavior of the scanning strategies on a more abstract level. It may be noted that in this view we do not see spatial information in the sense that we know where in the 2D stimulus we are located over time. The connection to the stimulus is completely lost, but can be regained by looking at the aligned color bands that give a hint about the positions of the eyes in the displayed stimulus. For more detailed information about the exact spatial position we can have a closer look at the original stimulus which is interactively linked with all of the views.

The metrics timeline also reads from left to right. It consists of color coded circles that indicate the fixations at specific time points while the size and color equally reflect the fixation durations. The saccades are proportionally mapped on top of the circles (supporting interactively changing the line representations into tapered or non-tapered ones for indicating the directions) , i.e., they have a certain length and also a certain orientation which is observable by following the metrics timeline. This extra view on the saccadic information can already give a hint about the reading strategies, for example, if someone always looks in the same or similar direction or if a person is frequently changing this direction. For example, following a straight line by the eyes might be detected by many subsequent saccade directions. Also the lengths of the saccades are useful information in this plot. They indicate if people's eyes move over longer distances (and into what direction) or if they rather prefer to do small movements, for example when reading text.

Figure 2 illustrates the metrics timeline for the same scanpath given for the color bands (Section 4.2). We see that most of the saccades are more or less vertically oriented and the lengths are varying a lot over time. For the fixation durations there are two longer fixations while the longest fixation duration is the last one (rightmost gray colored circle). We can also get an impression about the distribution of fixations over time. In this diagram there are not many longer gaps, like if someone has to fixate very long to understand the semantics of a stimulus. Many insights can already be derived from this individual plot, but even more can be found if the metrics timeline is combined with the aligned color bands.

The metrics timeline is useful for problematic scenarios like if someone is fixating the same or similar point many times (SO1). Then we see many fixation points while the saccades are pretty short. Longer eye jumps can be detected by observing the saccade lines (SO2). Oscillating visual attention behaviors can be detected by looking for saccades being oriented in opposite directions (SO4). With the metrics timelines it is not possible to see if the eyes left the display or the stimulus (SO3) while also fixation distances can only be judged for neighbored points but not for all pairwisely (SO5).

4.4 Distance Arcs

The bottom view adds another perspective on the eye movement data. The spatial distances in the stimulus can change a lot over time, meaning a participant might for example regress back to formerly seen elements in the stimulus or the formerly seen points are never inspected again. Showing this information in a traditional eye movement data visualization can become problematic due to overplotting and visual clutter issues. Moreover, our perceptual and visual system is only efficient in judging the distances between neighbored points, connected by a straight line, but pairwise distances require to virtually add those lines to reliably judge the distances.

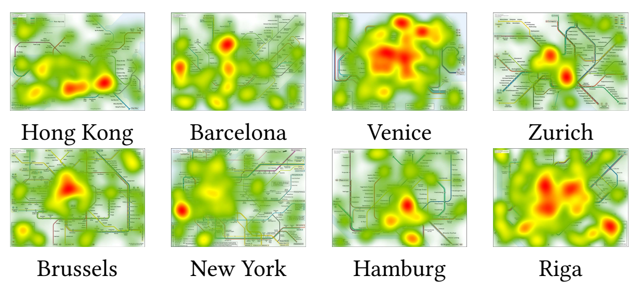


Figure 4: Example metro maps overplotted with visual attention maps. We can see that there are different visual attention patterns depending on the map itself but also on the route finding tasks. In these scenarios we can neither detect any dynamic scanning strategies nor can we compare them over space and time: Hong Kong, Barcelona, Venice, Zurich, Brussels, New York, Hamburg, Riga.

To also see this data aspect we provide distance arcs that reflect by their color coding how far apart two fixation points or two areas of interest are. This can also be useful to detect those distances over time while they are set in focus to other spatial and metrics-related data aspects. We used arcs instead of straight lines to perceptually help the viewer with linking start and end points of the distance indicators (in this case arcs). A triangular matrix [Kasprowski and

(a) (b) (c)

Figure 5: The metro map of Barcelona in Spain in three different settings: (a) The map in its original form. (b) The color coded map overplotted with a visual attention map for all study participants. (c) A grayscale map overplotted with a visual attention map for all study participants.

Harezlak 2017] would also be a solution but then the correspondences of the distances to start and end fixations are hard to find. Although these arc diagrams produce overlaps and visual clutter they are still useful to get a coarse overview about fixation distances. Moreover, the distances might also change over time which is also derivable by the arc diagrams, in particular if interaction techniques are applied to filter the distances for certain criteria.

Figure 3 illustrates the same scanpath as in the color bands and the metrics timeline views while it now depicts the pairwise Euclidian distances between the fixation points represented in a linear optimal color scale. We are only interested in the distances of the direct neighborhood, i.e., we only look at the 10 next fixation points. This parameter can be modified interactively. We can easily see that in the beginning the color of the arcs seems to be much brighter indicating that in the beginning many more fixations were done spatially far apart. Maybe the participant first had a look over the stimulus to build something like a mental map before starting to answer the given task. This dynamic pattern changes over time, i.e., towards the end the arcs have a darker color showing that the viewer inspected more regions in the direct neighborhood in the stimulus.

The distance arcs can be useful if similar points over time are fixated. Then the distances remain similar and only slightly change (SO1). Longer eye jumps can be observed by looking at the color coding of the arcs. Moreover, we can see if the eye moves back again since we can inspect all pairs of fixation distances (SO2). Oscillating behavior is also derivable by typical dynamic arc patterns (SO4). The view is explicitly designed for the fixation distances and hence, has most of the benefits if someone is interested in dynamic distance behavior, also supported by interactive filtering (SO5). The only problematic issue with the arc diagrams is the fact that we cannot easily detect if the eye leaves the display or the stimulus (SO3).

5 APPLICATION EXAMPLE

We applied our approach to eye movement data from a formerly conducted eye tracking study by Netzel et al. [Netzel et al. 2017] for which the data is publicly available. The participants had to answer route finding tasks in color coded and grayscale public transport maps while telling the interchange points.

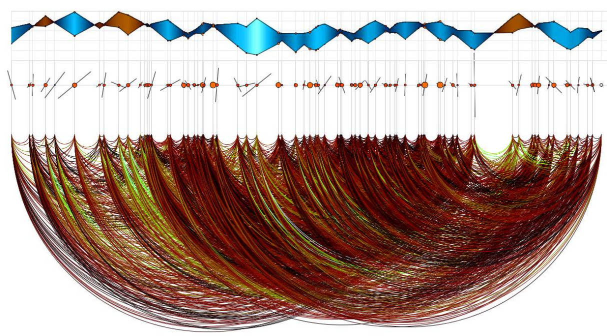


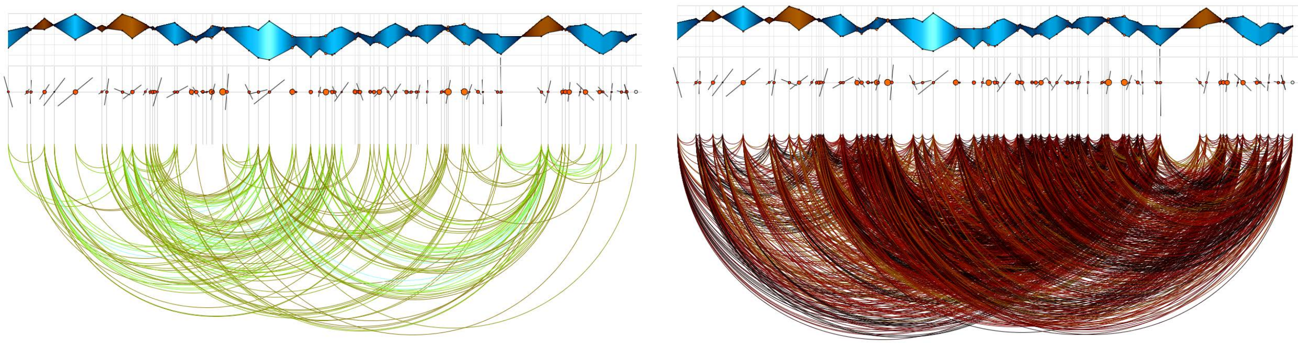
Figure 6: A visual encoding for a scanpath of one participant while trying to find a route in the public transport map of Barcelona in Spain. The fixation distances are already filtered by the fixation neighborhood in the sequence (at most 50 fixations away) otherwise the visual clutter effect would be too strong.

5.1 Overview

Netzel et al. [Netzel et al. 2017] show 24 different metro maps from cities all over the world. The map stimuli are real-world scenarios designed by a professional map designer from Communicarta Ltd., all maps have similar characteristics.

Figure 4 shows some of the example maps used in the eye tracking study. All the maps are overplotted with visual attention data from the study and shown as visual attention maps. From such an overview, an exploration process can be started that gives more insights into the dynamics of the visual scanning strategies. Moreover, comparisons over space and time can be done, while with visual attention maps only a spatial comparison between stimuli or participants is possible.

We choose the metro map of Barcelona in Spain (see Figure 5) from the repertoire of maps and load the recorded eye movement data into our tool. The output in form of a visualization can be seen in Figure 6. Here, we already filtered for neighbored fixations in the scanpath since otherwise the diagram would be much too cluttered to see anything. We only take into account the distances of fixation points that are at most 50 fixations apart from each other.



(a) (b)

Figure 7: The distance values can be filtered for value ranges. This scanpath consists of more than 60 fixations: (a) All distances greater 500 units are displayed and color coded. (b) All distances smaller or equal to 500 units are displayed.

Figure 6 already shows some interesting patterns. From the color bands view we see for example that this study participant mostly looked at points with a low x-coordinate but a higher y-coordinate (by the blue color coding). Only in three short time periods the color switches to brown which means the y-coordinate is lower than the x-coordinate. The participant also never looked into the corner of the display. Otherwise we must see combined maximum and minimum x- and y-values, but this is not the case. The participant started with lower coordinates in the beginning and later x- and also y-values become a bit higher, but also some looking back strategies can be found. The metrics timeline for this participant and the metro map of Barcelona is interesting. In the beginning the saccade lengths are longer than towards the end. This is the case for nearly all participants and nearly all metro maps. The reason for that might be that the participants do not exactly know what to do in the beginning, consequently, they start with first building some kind of mental map which causes their eyes to frequently move around (this also explains the brown color in the color bands in the beginning). The saccade orientations do not follow a clear strategy like we would expect when following lines (like in metro maps). But it seems as if they change their trend a bit from lower left to upper right and now upper left to lower right. Moreover, there are nearly no horizontally oriented saccades.

The fixation distance arcs show a strange pattern. It seems as if the arcs can be separated into two different components (one in the beginning and one in the end). The ones in the beginning show more light colors while the later ones have more brown colors. The dark color indicates shorter distances while the lighter color reflects long distances. But this finding is in line with the findings from before since in the beginning the eyes start scanning around to build the mental map to solve the task and hence, they more or less jump over the stimulus. This explains the lighter color codings of the arc in the beginning. There is also one phase close to the end exactly there where the outlier is located. After the long fixation and with the long saccade the eyes move over a long distance, a fact that can also be seen in the color bands since the color there is changing from blue to brown.

5.2 Distance Value Thresholds

To further reduce the amount of visual clutter and to apply some interaction techniques we now filter the distance-based arc diagram by distance value ranges. To reach this goal we filter out all arcs that indicate a threshold smaller or equal than 500 units and only display the remaining ones (all arcs greater than 500 units). This can be seen in Figure 7 (a). On the other hand and for comparison reasons we also show all distance arcs that indicate a distance value of less or equal than 500 units and show those next to it for comparative reasons (see Figure 7 (b)).

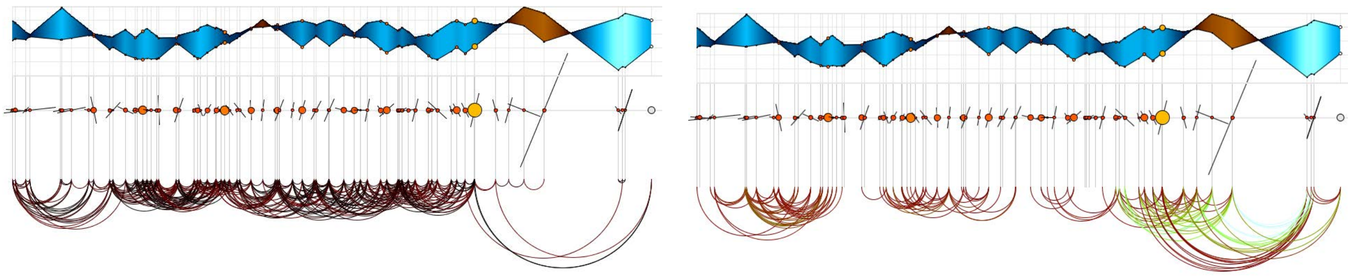
Looking at the arc diagrams we can easily see the difference and even there we can get some more insights. There are more shorter eye movements than longer ones (in this case more or less than 500 units). This means the given task in the eye tracking study seems to be solved by mostly moving between neighbored points but sometimes also longer eye movements have to be made, for example, to check a partial solution in the route finding task.

5.3 Sequence Neighborhood

For the distance values we could also restrict the neighborhood parameter in the fixation point sequence. This means only those arcs are displayed that lie in the direct neighborhood given by that threshold parameter. All others are neglected. This filter reduces the amount of visual clutter tremendously and reflects if there are longer eye movement distances between neighbored points in a sequence which means the eyes may have moved to a totally different region on the stimulus.

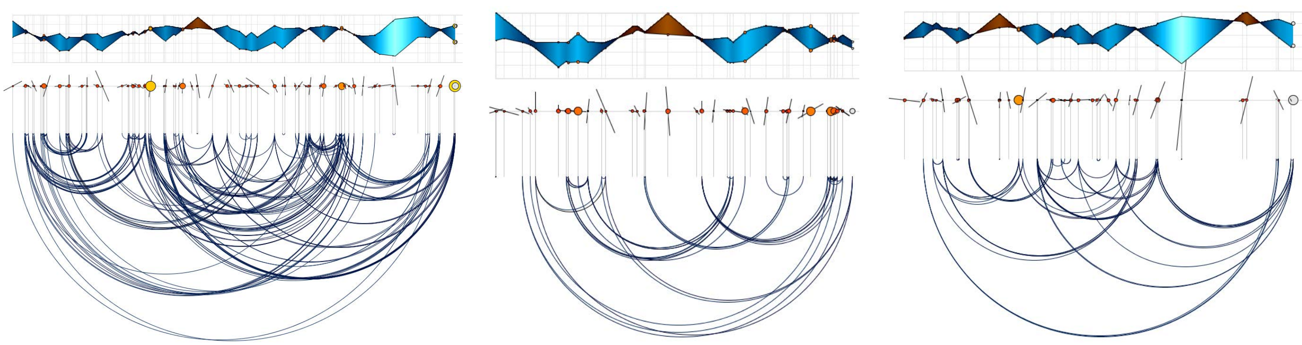
But also the opposite effect might happen, i.e., between neighbored points the eyes only make shorter distances meaning there is probably a clear and smooth strategy the eyes are able to follow to solve the given task.

Figure 8 (a) shows a scenario in which short distances are indicated for a neighborhood of at most 10. In (b) we can see that there are also longer distances when the same neighborhood parameter is applied. It seems as if this participant (which is another one than the one before) had much more problems to follow the path with his eyes than the participant whose eye movements we explored before.



(a) (b)

Figure 8: Only distance arcs for the next 10 neighbors are displayed. This scanpath consists of more than 50 fixations: (a) A distance value threshold of less than 100 units is applied. (b) A distance value threshold of more than 100 units is applied.



(a) (b) (c)

Figure 9: The eye movements of three different participants while answering a route finding task in the same public transport map. We can see similarities in the color bands indicating that the participants followed similar dynamic scanning strategies. Inspecting the distance arcs to see if they went back and forth shows that the participant in (a) did much more cross checking than the others in (b) and (c).

5.4 Participant Patterns

There are many parameters one might like to change and to generate visualizations from. For example, we could also have a look into different participants and which visual scanning strategies they apply for the same stimulus and the same task.

Figure 9 shows three different participants and the corresponding visualization. The visual patterns in the color bands reflect many similarities, i.e., the shapes and color codings look similar. In (a) we see that the participant made many more fixations to solve the task than those in (b) and (c). Also the distance arcs are much denser indicating that the participant in (a) made many more chaotic movements back and forth. Maybe there was a problem in solving the task or the map was too difficult to understand.

Looking into extra data concerning the outcomes of the tasks, we can soon find out that the participant in (a) did not answer correctly. This means it may indeed be visible in the visualization that this participant had problems with finding the correct solution. The other two participants answered correctly.

6 CONCLUSION AND FUTURE WORK

In this paper we described a combined and linked visualization for eye movement data. It consists of three views focusing on visually encoding spatial data aspects, metrics-based aspects, and distance-based ones. All of the aspects have a time-varying nature and hence, we designed a temporally aligned visualization. Moreover, the approach is focusing on comparing eye movements over space and time which demands for transforming the spatial information from the visual stimulus into a more linear representation to avoid clutter, overdraw, and occlusion effects with the stimulus, but also with the scanpath themselves. The visual depiction of the data is supported by interaction techniques for aggregating over time or for filtering for certain time periods or value ranges. We applied the visualization technique to data from a formerly conducted eye tracking study investigating the readability of public transport maps while participants had to answer route finding tasks. For future work we plan to add more statistical data aspects to the visualization techniques and plan to research the applicability of our approach to dynamic stimuli like videos, animations, or interactive displays.

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