

Visual Comparison of Eye Movement Patterns

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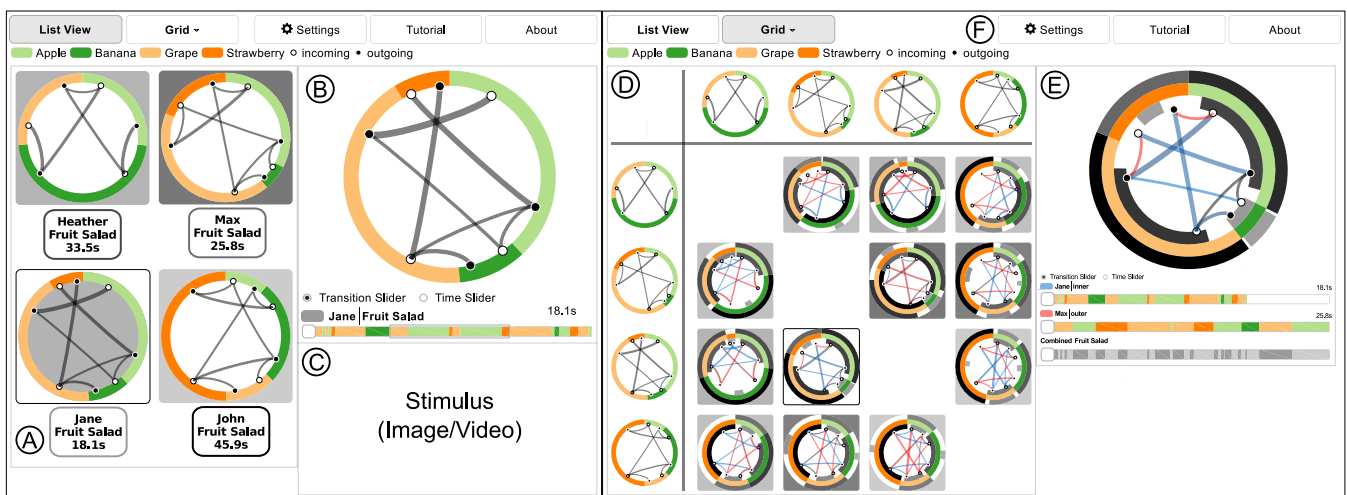


Figure 1: Visual comparison of eye movement patterns using radial transition graphs. A) The Comparison List View with an overview of all transition graphs. B) The Radial Transition Graph View shows one transition graph and transition sequence. C) A placeholder for the stimulus of a study. D) The Comparison Grid View to visually contrast multiple transition graphs. E) The Transition Graph Diff View to compare two transition graphs. F) The toolbar to switch between views.

Abstract

In eye tracking research, finding eye movement patterns and similar strategies between participants' eye movements is important to understand task solving strategies and obstacles. In this application paper, we present a graph comparison method using radial graphs that show Areas of Interest (AOIs) and their transitions. An analyst investigates a single graph based on dwell times, directed transitions, and temporal AOI sequences. Two graphs can be compared directly and temporal changes may be analyzed. A list and matrix approach facilitate the analyst to contrast more than two graphs guided by visually encoded graph similarities. We evaluated our approach in case studies with three eye tracking and visualization experts. They identified temporal transition patterns of eye movements across participants, groups of participants, and outliers.

Categories and Subject Descriptors (according to ACM CCS): H.5.2 [Information Interfaces and Presentation]: User Interfaces—Graphical user interfaces (GUI)

1. Introduction

Eye tracking research is concerned with learning about participants' viewing behavior. Where participants look and in which or-

der parts of a stimulus participants focus on gives insights about task solving strategies. Visually comparing data from different recordings facilitates an analyst to identify typical patterns across participants. In this way, an analyst can identify participant groups sharing the same strategy and detect outliers. However, raw eye movement data—consisting of fixations, saccades, and changes in the stimulus—is complex. Abstracting fixation sequences in a meaningful way supports an efficient exploration of such patterns.

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We use Areas of Interests (AOIs), which are semantic regions on a stimulus according to a study task, to simplify the eye movement data and add semantic information to the analysis. Switches of participant's attention from one AOI to another become connections of AOIs in a transition graph. Comparing AOI transition graphs now promises to study eye movement patterns across different recordings on this high level of abstraction including stimulus semantics. In the scope of this paper, we define an eye movement pattern as a set of AOI transitions recurring in the same or similar way across different participants or within the temporal sequence of a single participant. Current techniques only show single AOI transition graphs without providing details of differences between graphs [BKR*16, HHBL03, KW15, TAK*05]. Others contrast AOI sequences as part of a hierarchy or timeline representation that either aggregates the individual recordings or do not explicitly hint at differences and similarities [BKW13, KW15, RCE12, TTS10].

In this application paper, we use transition graphs with a radial layout [BRE13] that enable a direct comparison of two or a pairwise comparison of more than two participants. We complement our approach with timelines to also compare the dynamic viewing behavior of two participants. Figure 1 shows the different views of our approach. The combination of views and visualizations enables an analyst to extract participant groups of similar viewing behavior, to visually compare between transition graphs, to find similar or different ones, and to contrast temporal differences.

We evaluated our approach with three experts in eye tracking and visualization research. The experts worked with eye movement data they recorded in their own experiments. Based on first feedback the experts gave, we iterated on our approach and extended it. A second evaluation with the same three experts revealed that our extensions considerably improved the first version. We showcase observations our experts gained from their data using our approach as examples.

The interactive visual comparison approach is available online[†] with all data sets used in the main evaluation. The supplemental material contains the questionnaire of the main evaluation and a video explaining the approach in detail.

2. Related Work

Our work is in scope of eye tracking as a research method and presents a visualization approach to evaluate eye movement data [BKR*17]. The main focus is to contrast different data sequences by means of visual comparison [GAW*11]. Since we abstract eye movements to temporally changing transition graphs, particular graph visualization and comparison [vLKS*11] as well as dynamic graph visualization [BBDW17] provide relevant techniques we are building on and extending.

Transition graphs are one of the standard visualization approaches for eye movement data [BKR*17, 6.3. Relational AOI Visualizations]. This form of eye tracking visualization is closely related to movement data visualization [AABW12], where trajectories can be interpreted as a graph as well, and dynamic graph visualization [BBR*14], where relational information changes over time.

Typically, a transition graph is visualized as a node-link diagram, either overlaid on top of a static stimulus [HHBL03] or plotted independently of the stimulus [TAK*05]. Our approach extends *circular heat map transition diagrams* [BRE13], a node-link diagram in a radial layout encoding dwell times—the total time a participant focused on an AOI—in ring sector size and color. However, this approach has only been used to show single transition graphs.

From a visual comparison perspective, our work applies an approach based on *juxtaposition* (i.e., placing graphs to compare next to each other) and *explicit encoding* (i.e., encoding differences explicitly in visual representations) [GAW*11]. A list view shows the individual graphs juxtaposed and an analyst can select pairwise comparisons on demand as already successfully applied in some examples [BMGK08, vLBR*16]. In addition, we use a matrix to encode $n \times n$ pairwise differences between n graphs, as it has been demonstrated for time series [SLKS12]. In the pairwise comparison, our approach shows both differences of aggregated transitions and dynamic sequences of fixations.

Comparison of AOI transitions of different participants or sources has focused on representing the eye movement data in matrices, trees, or timelines. Matrix approaches either aggregate the transition data of multiple participants [BKR*16] or allow a comparison by concatenating participant's transition data and coloring matrix cells where equal transitions occur [GH10]. Similar comparison approaches with colored matrix cells have been investigated in other applications as well [ABZD13, BD13, MGK11]. Representing transition information as AOI or transition trees of multiple participants can either show only short sequences [KW15, TTS10] or again has to aggregate the data [BKR*16]. Our approach, in contrast, uses node-link diagrams as a basis for comparison. For showing and comparing temporal information, typically, scarf plots or AOI timelines are used [HNA*11, KBB*14]. Here, participants are compared by placing timelines below each other [AABW12, BJK*16], aggregating the data [BKW13], or drawing them on top of each other [RCE12].

For comparing two general node-link diagrams, previous work demonstrates that graphs can be shown as node-link diagrams in two views juxtaposed [vHvdWvW01], in two views with additional links between them [CC07], in three views showing the two original graphs plus a merged graph [AWW09, LD14], or in a single view encoding the difference of graphs [Arc09, KSB*16, ZKS11]. As an alternative representation, two graphs might be compared in a single adjacency matrix representation, for instance, encoding edges differently within the cells [ABHR*13, BD13]; MatrixWave [ZLD*15] extends this approach to comparing two event sequences. However, we want to compare more than two graphs. Options to extend the comparison are to juxtapose aligned node-link diagrams with interactive possibilities to create merged graphs [BPD11] or small multiples using a diff view [vLBR*16]. Regarding the area of application, particularly related are those approaches comparing movement trajectories in a graph difference view [KSB*16, vLBR*16] because eye movements can be considered as trajectories [AABW12]. There also exists work specialized on the comparison of state transition graphs [BBG*09, vHvdWvW01]. We are not aware of any node-link comparison methods specializing on AOI transition graphs.

[†] Radial Transition Graph Comparison Tool: <http://www.rtgct.fbeck.com/>

To specify a tailored method for transition graph comparison, we hence build our work on established visual comparison concepts to contrast multiple graphs in an overview and show on demand pairwise differences in detail. However, transition graphs—abstracting a temporal trajectory—are inherently dynamic [BBR*14], but this dynamic has not been considered in literature on graph comparison. There exist many approaches to visualize a single dynamic graph [BBEW17], but we are only aware of a single approach that compares two dynamic graphs [Bur16]—the axes of a matrix represent the sequence of changing graphs with difference encodings of the graphs in the cells. Although our comparison grid visually resembles this approach, we employ a matrix for a comparison of static graphs only and compare the dynamic graphs in a diff view using sliders. This slider-based comparison solution is a novel contribution to the challenge of dynamic graph comparison.

3. Design Considerations

Before we describe our approach in detail, we define important terminology and introduce a formal data model. We then infer three eye tracking analysis tasks and compare them to state-of-the-art techniques.

3.1. Terminology and Data Model

Collecting eye movements results in a sequence of fixations. Fixations occur when a participant focused on a specific location for a certain amount of time. Between fixations, rapid eye movements take place, called saccades. A sequence of fixations and saccades is a scan path. To compare scan paths of multiple participants, we abstract a scan path using AOIs. AOIs are regions on a stimulus of interest. Typically, AOIs can be of any geometric shape and we do not restrict AOIs to a static location on the stimulus (e.g., moving AOIs in a video are also possible). We define a set of AOIs $A = \{a_i\}, i = 1, \dots, k$ where a_i describes an individual AOI. Fixations are mapped to AOIs and are aggregated into dwells. A dwell characterizes “one visit in an AOI, from entry to exit” [HNA*11]. This set of dwells $D = \{d_j\}, j = 1, \dots, m$ contains a dwell d_j , which is defined as a triple $d_j := (ts_j, te_j, a_{\lambda_j})$. A unique AOI a_i is assigned to each dwell d_j with $\lambda_j = i$. The start time ts_j and the end time te_j are subtracted to derive the dwell time $t_j := te_j - ts_j$. Summing up all dwell times t_j , we infer the aggregated dwell time T_i of an AOI a_i :

$$T_i := \sum_{j \in X_i} t_j, \quad X_i := \{j | d_j \in D \wedge \lambda_j = i\}.$$

The total dwell time is the sum over all k AOI dwell times:

$$T := \sum_{i=1}^k T_i.$$

For a wide applicability of our approach to a static stimulus (i.e., an image) or a dynamic stimulus (i.e., a video, an interactive interface, or a real-world scenario), we use a graph as a data representation independent of the stimulus. We define a transition graph as $G = (V, E)$, where the AOIs are the vertices ($V = A$). The directed edges between AOI vertices are the transitions. Transitions are added as edges to the graph if a “movement from one AOI to another” is detected [HNA*11]. We define the edges as

$E = V \times V \times \mathbb{N}$ with $e_{pq} = (a_p, a_q, w_{pq}), p \neq q$. We specify the transition count of an edge as the weight w_{pq} :

$$w_{pq} := |\{j | d_j \wedge d_{j+1} \in D \wedge \lambda_j = p \wedge \lambda_{j+1} = q\}|.$$

Our application can be used to represent data of one participant for one stimulus with different activities, data of one participant for multiple stimuli, data of multiple participants for one stimulus, or data of multiple participants and multiple stimuli where the AOIs are the same. Each individual participant or activity is represented by an individual transition graph.

3.2. Tasks

Based on previous work and our own experience on visual comparison of graphs, the visualization of eye movement data in general, and of AOI graphs in specific, we came up with three tasks and three subtasks. Task T1 covers what previous work already supports, focusing only on a single graph. Simple visual comparison approaches of two graphs (Task T2) and advanced approaches further support the comparison of more than two graphs (Task T3). From standard AOI graph visualization techniques, we know that AOI dwell times (Subtask a) and AOI transitions (Subtask b) are important. Exploring temporal AOI sequences (Subtask c) is a task often covered by AOI visualization techniques. This combination of three tasks from visual comparison and three tasks from AOI visualizations leads to a total of nine tasks with a three by three structure:

Task T1. Explore a single transition graph G_1 , in particular, its (a) dwell times, (b) directed transitions, and (c) temporal AOI sequences.

Task T2. Compare two transition graphs G_1, G_2 regarding their different (a) dwell times, (b) directed transitions, and (c) temporal AOI sequences.

Task T3. Find groups of similar transition graphs and outliers among n transition graphs G_1, \dots, G_n regarding their (a) dwell times, (b) directed transitions, and (c) temporal AOI sequences.

These three tasks are not novel and other approaches exist that support them to a certain extent. Table 1 shows the current state-of-the-art of AOI-based eye movement visualizations in comparison to our approach according to the personal opinion and experience of the authors. A node-link AOI graph [HHBL03, BRE13] is best applied to a single participant when analyzing dwell times and directed transitions. Using juxtaposition, this approach can to some degree also be used when comparing two or n participants. Similarly, the transition matrix [GK99], an adjacency matrix representation of the graph, covers the same tasks as the AOI graph. However, its main purpose is to depict directed transitions. Transition trees [KW15, TTS10] and dotplot matrices [GH10] can be used to show and contrast AOI sequences for one, two, or multiple participants. Although, the two techniques cover similar tasks, they have different purposes. Transition trees show in an aggregated form which AOI sequences participants share, whereas a dotplot matrix highlights similar AOI sequences between two participants. AOI timelines [HNA*11, ITS00] are best used for showing directed transitions, but an analyst can also inspect AOI se-

Table 1: Comparison to state-of-the-art techniques for eye movement data based on our three tasks with subtasks.

Legend: ○ = not supported, ◐ = partially supported, ● = supported

Task	AOI graph [HHBL03, BRE13]	Transition matrix [GK99]	Transition tree [KW15, TTS10]	Dotplot matrix [GH10]	AOI timeline [HNA*11, ITS00]	Scarf plot [KBB*14, HNA*11]	Our approach
T1 a	●	◐	○	○	◐	●	●
T1 b	●	◐	○	○	●	◐	●
T1 c	○	○	◐	◐	●	●	●
T2 a	◐	◐	○	○	◐	●	●
T2 b	◐	●	○	○	●	◐	●
T2 c	○	○	●	●	◐	◐	●
T3 a	◐	○	○	○	○	◐	●
T3 b	◐	◐	○	○	◐	○	●
T3 c	○	○	●	●	○	◐	○

quences and estimate dwell times of individual AOIs. Again juxtaposition allows to compare two or multiple participants. However, an analysis of directed transitions is only possible to a certain extent. Scarf plots [KBB*14, HNA*11] are best applied to analyze dwell times and AOI sequences. Similar to AOI timelines, they can contrast two or multiple participants, but its applicability also decreases the more participants are compared. In comparison to these techniques, our approach, developed to cover the individual tasks, uses AOI graphs and scarf plots, covering eight of nine tasks to a full degree. The only exception is Task T3 c showing AOI sequences for n transition graphs. Although other techniques, like the transition tree and dotplot matrix, could have been another addition, we did not include it into our current approach, because we wanted to avoid visual clutter in the Comparison Grid View. Our main focus in this application was on directed transitions and dwell times, whereas comparing temporal AOI sequences was only added later based on user feedback.

4. Visualization Approach

Our visual graph comparison approach uses transition graphs for analyses of eye movement data to find temporal transition patterns across participants, groups of participants, and outliers. Based on n transition graphs juxtaposed as small multiples in the *Comparison List View* (Figure 1 A), an analyst can inspect one transition graph with the *Transition Graph View* in detail (Figure 1 B, Task T1), compare two transition graphs using explicit encoding in the *Transition Graph Diff View* (Figure 1 E, Task T2), and a selection of graphs with $n \times n$ pairwise comparisons using the *Comparison Grid View* (Figure 1 D, Task T3).

In addition to the four views, a static stimulus or a video of a study can be loaded (Figure 1 C). Also, an analyst can upload a video for each individual transition graph to inspect the collected eye movement data recorded for a participant. A toolbar is available to switch between the *Comparison List View* and the *Comparison Grid View* (Figure 1 F), change settings, and open a tutorial

explaining each view. Our approach is a web-based application implemented using JavaScript and the D3.js library.

Throughout this section, we use a simple artificial example with four participants to explain each view. The four participants are Heather, Max, Jane, and John. The stimulus contains the AOIs *apple*, *banana*, *grape*, and *strawberry*. This example could represent data recorded from a static stimulus where participants investigated an image of a fruit basket or a dynamic stimulus where participants wearing eye tracking glasses went into a supermarket to inspect different fruit racks. In this section, we present the final visualization approach after collecting feedback in a preliminary evaluation with three eye tracking and visualization experts (Section 5).

4.1. Transition Graph View

The transition graph visualization (Figure 1 B) is based on the work of Blascheck et al. [BRE13]. Our version of the node-link diagram with a radial layout uses ring sectors for each AOI. AOIs are ordered alphabetically or by assigning them an explicit order ID. There are two different modes for the ring sector sizes. Either the size of the ring is constant or relative to the dwell time T_i of an AOI a_i to the total dwell time T : $rs_i := 2\pi r \frac{T_i}{T}$, with radius r . With this feature, we support the exploration of dwell times of a single transition graph (Task T1 a). Drawing all AOIs with the same size is referred to as *equal sector mode* and eases comparison of transition graphs, for example, to find similarities between them based on their directed transitions (Figure 4). Instead of encoding the fixation count into the color of the ring sector as in the original approach [BRE13], we decided to give each AOI a unique color. A unique color is important to match the same AOIs across multiple views. In all our examples, the original data has four to five AOIs. If the number of AOIs is more than about a dozen, a selection of AOIs beforehand might be necessary, for example, by selecting a specific scene in a video or grouping AOIs semantically [BKR*16]. We use a color scheme from ColorBrewer [HB03] for categorical data, with an alternation of dark and light colors to better see changes in the scarf plot explained below.

In the ring center, transitions e_{pq} between AOIs are visualized. The transition lines are drawn as arcs for a better readability, especially for transitions between two neighboring AOIs. The arc thickness represents the transition count w_{pq} logarithmically scaled. We separate the directed transitions into incoming and outgoing transitions and use two anchors: a white circle for incoming transitions and a black circle for outgoing transitions. With two separate anchors for transitions, we do not need arrow heads avoiding visual clutter with multiple transitions. This feature covers an exploration of a single transition graph based on directed transitions (Task T1 b). Additional information about AOIs and transitions is shown on demand in a tooltip (Figure 2). For AOIs, the tooltip contains the name and dwell time. The name of the start and end AOI and the transition count are shown for transitions.

The exact temporal order of transitions is lost when showing only the transition graph. Therefore, we added a scarf plot [HNA*11, KBB*14] at the bottom of each transition graph in the *Transition Graph View* (Figure 1 B). The sequence of AOIs is depicted by drawing colored rectangles in sequence. The color corresponds

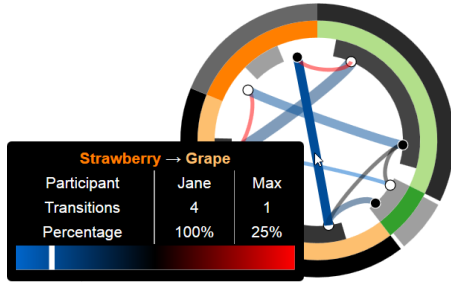


Figure 2: The tooltip of a merged transition shows details about the connected AOIs, compared participants, and the resulting color coding of the transition.

to the AOI and the width to the dwell time. This plot enables an in-detail temporal investigation of transitions to find patterns (Task T1 c). The name of the participant, the stimulus name, the dwell time with the exact number value and encoded as a rectangle are shown above the scarf plot. The rectangle is drawn with a gray to black color scale, where black represents the maximum total dwell time. An analyst can interact with the scarf plot using sliders and either select individual transitions (*transition slider mode*) or time ranges (*time slider mode*). The transition slider has one indicator to select individual transitions in the transition graph. The time slider has two indicators to restrict the time range of transitions depicted in the transition graph.

4.2. Comparison List View

The *Comparison List View* gives an overview of all transition graphs in a juxtaposed small multiples approach (Figure 1 A). An analyst can inspect all transition graphs and visually compare them to find similar or different transition graphs. Below each transition graph, an information panel shows the participant ID, the stimulus name, and the total dwell time. Additionally, the total dwell time is encoded in the border of the information panel using a gray to black color scale, where black represents the maximum dwell time.

To improve the comparison process, we additionally calculate a visual graph similarity metric between transition graphs. A selected transition graph is represented with a black border and the background of all other transition graphs represents the similarity relative to the currently selected transition graph. The background is shaded with a gray to black color scale, where black represents a similarity of 1. It represents the similarity relative to the currently selected transition graph. In Figure 1 A, Jane is selected and Max's transition graph has the highest similarity to Jane's. The similarity of two transition graphs is determined by first calculating the difference. The difference is calculated by subtracting the transition counts w_{pq_1}, w_{pq_2} between two AOIs a_p and a_q and summing the absolute difference for all pairs of AOIs of the two transition graphs. Then, the sum of the differences is divided by the total weight of all transitions for both transition graphs:

$$d := \frac{\sum_{pq} (|w_{pq_1} - w_{pq_2}|)}{\sum_{pq} (w_{pq_1} + w_{pq_2})}.$$

As the difference function returns values between 0 and 1, where 0 means no difference and 1 means total difference, we invert the

value to the similarity $sim = 1 - d$. We solely base the similarity on the transition weights because our approach focuses on a comparison of transitions. However, other metrics are possible, for example, a measure based on dwell times or a combination of transition weights and dwell times. The exact similarity value of two transition graphs is available in a tooltip.

4.3. Transition Graph Diff View

When dragging one transition graph onto another in the *Comparison List View*, the *Transition Graph Diff View* is shown on the right (Figure 1 E). It uses an explicit encoding to depict differences between two transition graphs. For example, if we drag the transition graph of Jane onto Max's, the transition graph presented in Figure 1 E is generated. The size of the colored AOI sectors rs now depends on the maximal dwell time of each AOI a_i of the two transition graphs G_1, G_2 :

$$T_{max} := \sum_i^k \max(T_{i_1}, T_{i_2}), \quad rs_i := 2\pi r \frac{\max(T_{i_1}, T_{i_2})}{T_{max}}.$$

Additionally, an inner and outer ring are added for the two transition graphs being compared. The dwell data of the transition graph dragged onto the other is shown on the inside, the dwell data of the other on the outside. In the example, Jane's dwell data is on the inside, Max's on the outside. The outer and inner ring sector sizes are calculated based on the maximum size of each ring sector:

$$in_{i_1} := 2\pi r \frac{T_{i_1}}{T_{max}}, \quad out_{i_2} := 2\pi r \frac{T_{i_2}}{T_{max}}.$$

As Max has a longer dwell time on the *apple*, his outer ring is larger and the ring sector has its maximum size. Jane's ring sector is smaller because she has a shorter dwell time. The additional sectors show the dwell time for each AOI for the two compared transition graphs using a gray to black color scale, where black represents the maximum total dwell time of all AOIs $\max(T_1, T_2)$. This enables us to contrast two transition graphs based on their different dwell times (Task T2 a).

The transitions now represent the difference between both transition graphs. The arc thickness presents the maximum of the transition counts of both graphs $w_{pq} := \max(w_{pq_1}, w_{pq_2})$. The transitions are also colored based on the difference between the transition counts of both transition graphs $w_{pq_1} - w_{pq_2}$ using a hue-preserving color blending [CWM09] from blue to red (Figure 2). Because Jane has more transitions between the *grape* and *banana* AOIs, the transition is shown in blue. Max has more transitions between the *strawberry* and *apple* AOIs depicted in red. Both have the same number of transitions from the *apple* to *grape* AOIs shown by a gray transition. This enables a comparison of directed transitions (Task T2 b).

The temporal information is again depicted as a scarf plot below the transition diff graph. The inner transition graph's scarf plot is at the top and the outer is in the middle. A combined scarf plot is at the bottom and shows the union of transitions of both transition graphs, color coded alternating with a dark and light gray (Figure 1 E). Again, the scarf plot can be interacted with using the two modes: transition slider and time slider mode. This allows to find recurring transition sequences between two transition graphs (Task T2 c).

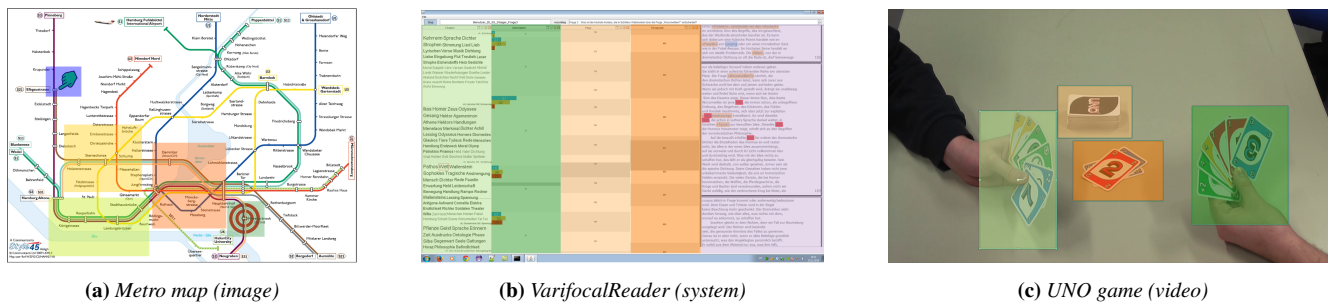


Figure 3: Images of the stimuli with AOIs used in the expert evaluation for each study.

4.4. Comparison Grid View

A complete comparison of all transition graphs using pairwise differences is available in the *Comparison Grid View* (Figure 1 D). Rows and columns of the matrix show all transition graphs. Each cell presents the diff between two transition graphs. The pairwise similarity of all transition graphs is depicted in the background using the same similarity measure as in Section 4.2. This visual overview of all transition graphs compared to each other allows to find similar transition graphs or outliers based on their dwell time and directed transitions (Task T3 a and b). In our example, Jane and John are the most dissimilar with a similarity value of 0.2. Max and Jane are the most similar with a similarity value of 0.53. Selecting an individual transition graph in a row or column or selecting a transition diff graph in a cell shows the corresponding transition graph in an enlarged version on the right.

The *Comparison Grid View* can be generated either showing all or individually selected transition graphs. A selection mode is available and transition graphs can be marked in the *Comparison List View* before opening the *Comparison Grid View*. This enables an analyst to select a subgroup of transition graphs which are further analyzed in detail instead of comparing all transition graphs.

5. Expert Evaluation

To evaluate and revise our approach, we conducted an expert evaluation in two sessions: a preliminary and a main evaluation. In both sessions, we asked the same three experts in eye movement analysis and visualization design for their opinion. In both studies, an observer was present who gave an introduction to the approach, took notes, and helped experts if they encountered an obstacle.

Preliminary Evaluation. The preliminary evaluation was intended to collect first feedback for our approach. All experts saw a version of the preliminary approach with the example data used in this paper and two saw data of their own eye tracking study. First, the experts were given an introduction to the system. Then, they used the interactive visual comparison approach themselves and made suggestions about how to enhance this first version. Recommendations were given based on a questionnaire the experts filled out in Google Forms. The preliminary evaluation took about 30 to 45 minutes per expert. Overall, two experts mentioned, that the approach needs some explanation and time to learn to be able to work with it. For example, knowing which transition graph is displayed

Table 2: Summary of the data sets used in the expert evaluation.

Study	Type	# AOIs	# Participants
Metro map [NOK*17]	static	5	20
VarifocalReader [BJK*16]	interactive	5	8
UNO game [KHW14]	dynamic	4	25

at the inside and outside of the transition diff graph was especially difficult for them. Therefore, we added a legend to show this information. One expert also noted that AOIs get small if they have a short dwell time. This problem was solved by adding the option to draw AOIs with equal sector sizes, which was a proposal of another expert. Additionally, an expert observed that the temporal sequence of transitions is lost in the transition graph. We addressed this recommendation with the scarf plot now placed below the transition graph. Another suggestion was that it would be helpful to calculate and display the similarity of transition graphs, which was added to the new version of the approach.

Main Evaluation. In the second evaluation, the focus was on what observations experts had from their data and how they used our approach. This time, all experts analyzed data from their own study. We applied a structured data exploration process. The main evaluation took about 1 hour to 1.5 hours. First, experts were given an overview of the approach and an explanation about the new features. Then, they had to solve three tasks all with the same instructions “Please analyze your data and report your findings in detail.” but each time using a different view. First, they were allowed to inspect their data working only with the *Comparison List View* and the *Radial Transition Graph View* (Task T1). They were then shown the comparison of two transition graphs using the *Transition Graph Diff View* (Task T2). Last, the *Comparison Grid View* was explained and the experts inspected the data with it (Task T3).

During the study, the experts again filled out a questionnaire in Google Forms. The first part of the questionnaire was about the individual views and observations they made during the analysis. The second part of the questionnaire contained general questions about the subjective rating of our approach. We have added the questionnaire as a PDF file to the supplemental material. We additionally recorded a screen and an audio stream to be able to go back to each experts’ findings afterwards. We present the observations the experts made for each task in the following. An overview of data sets used in the study is given in Table 2 and an example stimulus with AOIs is shown in Figure 3.

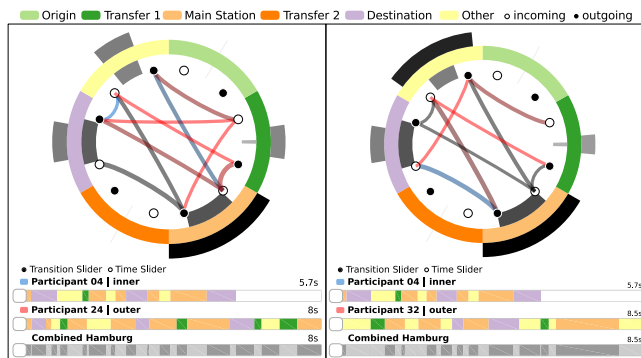


Figure 4: Detailed comparison using the Transition Graph Diff View and the equal sector mode to compare participant P04 to participants P24 and P32 in the metro map study.

5.1. Reading Metro Maps

The first data set is from an eye tracking study on reading metro maps [NOK*17]. The goal of the study was to analyze how participants find a way from an origin to a destination station using different metro maps of cities around the world. For the evaluation, one stimulus was picked to compare data of 20 participants solving the same study task. Each transition graph in the study represents one participant. The AOIs in the study were the *origin* and *destination* station as well as three transfer stations *transfer 1*, *transfer 2*, and *main station*. The stimulus with AOIs represented in different colors is shown in Figure 3a. The rest of the stimulus, not covered by AOIs, is considered as an *other* AOI.

Task T1 – Transition Graph View. Inspecting the *Comparison List View*, the expert first activated the equal sector mode, because this allowed him to find transition sequences visually. He then saw that participants P04 and P24 had a similar viewing behavior due to the parallel lines and transitions between the *other* AOI and the *main station* as well as the *other* AOI and *transfer 1*. Another finding was that 13 out of 20 participants did not focus on *transfer 2*. The expert confirmed that participants had two options to solve the study task, either using *transfer 1* or *transfer 2*. He also investigated cycles in the transition graphs and used the scarf plot and time slider in the *Radial Transition Graph View*. For example, participant P04 first looked at the *main station* and then at the *other* AOI back to the *main station*, and then to the *destination*.

Task T2 – Transition Graph Diff View. In the second task, the expert contrasted P04 with different participants. He found that this participant was similar to P24 and P32 using the similarity measure in the *Comparison List View*. A detailed comparison of P04 with these participants using the *Transition Graph Diff View* revealed different observations (Figure 4). For example, comparing P04 and P24 only indicates similar viewing behavior at the beginning. Contrasting participant P04 and P32 revealed that the transitions of P04 are a subset of the transitions of participant P32.

Task T3 – Comparison Grid View. The *Comparison Grid View* showed that participants P12 and P20 were outliers. Both participants had a dominating number of red/blue transitions, indicating their viewing behavior differed a lot from the other participants. Next, the expert selected a subgroup of participants (P01, P04, P16,



Figure 5: The Comparison Grid View of selected participants P01, P04, P16, P21, P24, P33, and P36 from the metro map study.

P21, P24, P33, P36) to compare them using the *Comparison Grid View* (Figure 5). This uncovered that most of the participants were similar, only participants P16 and P21 were not as similar.

5.2. Interactive Exploration of Text Documents

The second eye tracking data set is from an evaluation of the VarifocalReader [BJK*16]. The VarifocalReader is a hierarchical navigation technique of large document collections [KJW*14]. Eight participants were analyzed and each transition graph represents one participant. The AOIs are based on layers representing *chapters*, *subchapters*, *pages*, *paragraphs*, and *lines of text* of a book (Figure 3b). The parts of the stimulus not covered by an AOI are used as an *other* AOI. The task in the study was to find a specific text passage in a book navigating with the different layers.

Task T1 – Transition Graph View. The expert mainly used the time slider to inspect specific time ranges of participants. He picked participants of interest from the *Comparison List View* and then investigated them in detail in the *Transition Graph View*. The expert noted that participant P10 used the VarifocalReader in the way intended, first mainly viewing the *chapter* and *subchapter* and later the *page*. At the end, the participant focused more on the *lines of text* probably reading the appropriate text passage. This participant only looked at the *paragraph* for 6 seconds. Overall, either participants did not gaze on the *paragraph* at all or just shortly (Figure 6). This was an indication that the *paragraph* was not important to solve the study task.

Task T2 – Transition Graph Diff View. During the second task, the expert mostly compared participants whose data looked similar using the *Transition Graph Diff View* and the time slider. For example, he noticed P01 and P15 have a similar total dwell time (Fig-

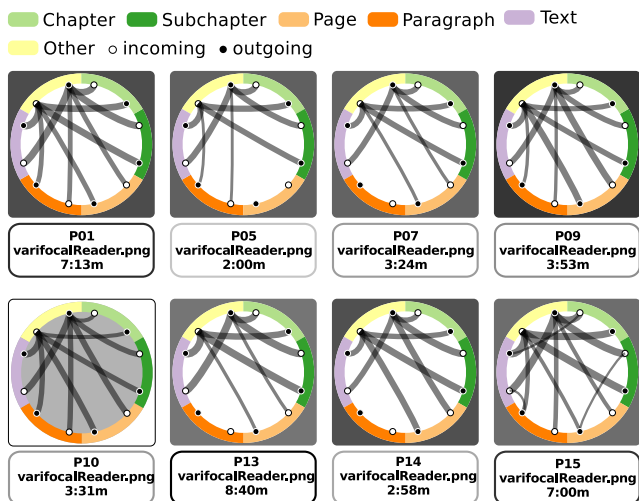


Figure 6: Data from the VarifocalReader study with participant P10 selected in the Comparison List View.

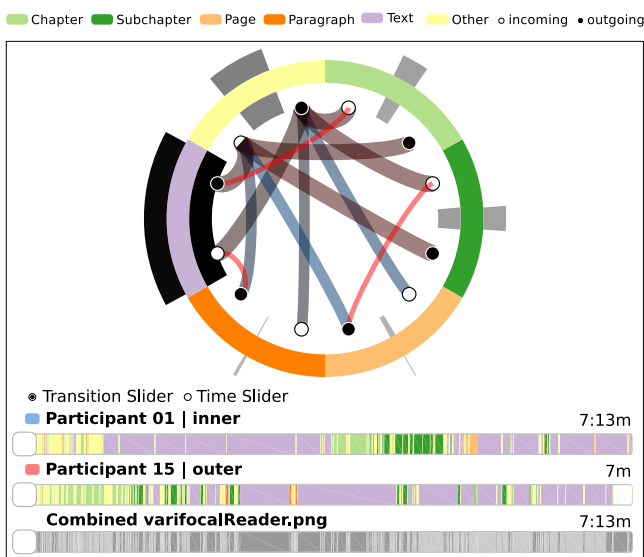


Figure 7: Data from the VarifocalReader study using the Transition Graph Diff View to compare participant P01 with P15.

ure 7). After excluding the beginning of the data of participant P01 using the time slider, most of the transitions were gray indicating a similar viewing behavior. The data of participants P14 and P09 was also similar, the only difference being that P09 looked at the *paragraph* whereas P14 did not. This viewing behavior was found for other participants as well.

Task T3 – Comparison Grid View. In the last task, the expert inspected the pairwise comparison of all eight participants using the *Comparison Grid View*. He suspected that participants P10 and P14 are the most similar. However, they were not, because P10 looked at the *paragraph*, had more transitions, and needed longer to complete the study task. Overall, the expert noted that the data of all participants seems similar. Only the data of participant P15 looked different, indicated by the dominating red/blue transitions.

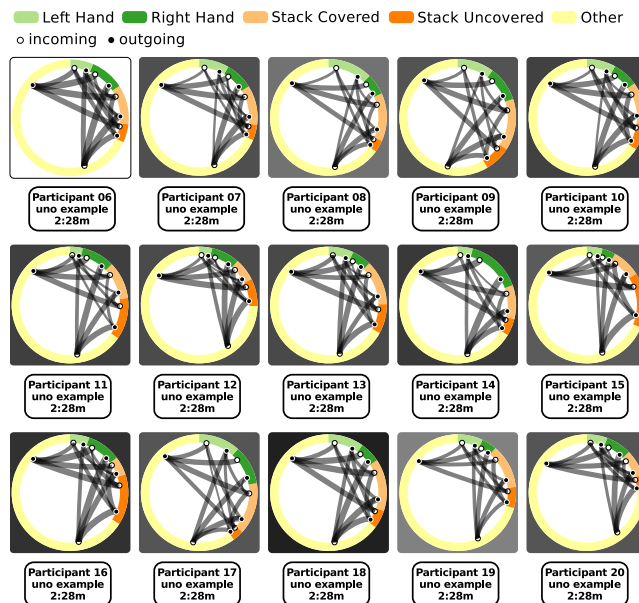


Figure 8: In the UNO game data set participant P06 is selected in the Comparison List View. Only participants P06 to P20 are shown.

5.3. UNO Game Video

The last data set evaluated is a study where 25 participants watched a video of two players playing a game of UNO [KHW14]. Each transition graph in the study again represents one participant. The total dwell time in this case is the same for each participant because it depends on the video duration. The AOIs are the *left hand* and *right hand* of the two players as well as the *covered* and *uncovered stacks* of cards (Figure 3c). Again, all fixations are assigned to *other* AOI if they do not have an AOI. In the video, the right player wins the game and the left player has to take many cards.

Task T1 – Transition Graph View. In the *Comparison List View* (Figure 8), the expert noticed that participant P20 in comparison to the other participants had less attention on the four AOIs. However, he also mentioned that it is hard to interpret the many dwells on the *other* AOI because this could either be a participant looking at the background not covered by an AOI or could be noisy data. Overall, for most participants, the number of dwells was equal for the *left hand* and the *right hand* with a slight tendency towards the *right hand*. Comparing the participants based on the amount of attention on the *covered* and *uncovered stacks*, P16 and P20 were striking because they had little attention on these AOIs. It seemed like they did not follow the game carefully.

Task T2 – Transition Graph Diff View. Using the similarity measure in the *Comparison List View*, the expert noticed that participants P06 and P07 were not as similar, having a similarity value of 0.69, as he would have expected from only comparing them visually. Participant P06 was more similar to the outlier P16 with a value of 0.81, P14 with a similarity of 0.78, and P18 with a similarity of 0.88 (Figure 8). However, only the transitions are considered to calculate the similarity values and not the dwell times as the expert initially expected. He then compared different participants using the *Transition Graph Diff View*.

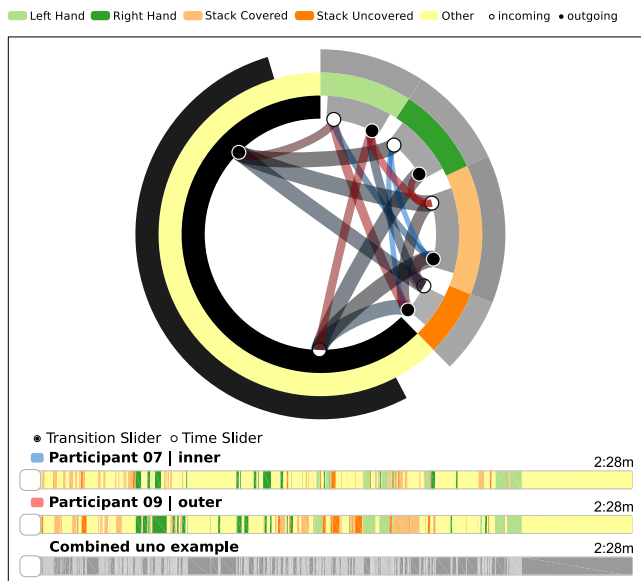


Figure 9: Comparing participants P07 and P09 using the Transition Graph Diff View for the UNO game study.

Task T3 – Comparison Grid View. Using the *Comparison Grid View*, the expert first inspected the pairwise comparison of all participants. However, it was challenging to find interesting transition sequences within all 25 participants. He then decided to pick all participants that have a similarity higher than 0.8 using participant P24 as the reference participant. Next, the expert selected these participants in the *Comparison List View* to only focus on these participants in the *Comparison Grid View*. He first thought there was no interpretation of why P07 and P09 are similar (Figure 9). However, inspecting these two participants in more detail, he found that both participants transitioned from the *left* and the *right hand* to the *covered stack*. He further noticed many transitions between the *uncovered* and *covered stack*, which was surprising to him. He would have expected a transition sequences from the *uncovered* to a hand AOI and then to the *covered stack*.

5.4. Qualitative Feedback

In the questionnaire the experts filled out, the last set of questions were more general. Experts could give multiple answers in free text form. We first asked if all comments of the first study were addressed and if not, which were still missing. All experts answered that all comments from the preliminary evaluation had been implemented. Next, we wanted to know if they thought this revision had improved. Two experts noted the similarity backgrounds as being helpful, two experts mentioned the time sliders, and one the temporal overview in form of a scarf plot. We also inquired about further suggestions for improvements they might have. One expert commented that the transition slider was not helpful, another noted that it could help to animate the transition slider or to set multiple time ranges with the sliders. The third expert suggested adding filtering options to the Comparison Grid View. Last, we asked what they thought is a realistic and suitable use case for our approach. The first expert answered that he “would use this tool for the initial evaluation of results of a pilot study, since there would only be few

participants with only few stimuli. For an actual study evaluation there would be too many single plots to compare, if someone would not know what he/she is looking for.” The second expert mentioned that he would use the approach to test hypotheses a software developer might have, for example, to find out that paragraphs of a text document are never used in the VarifocalReader study. The third expert would use our approach to search for similar behavior in context of transitions and try to find outliers.

6. Discussion

The first feedback helped us to improve our approach considerably. However, there are still limitations of the approach and possible extensions for the future. We also discuss how our approach might be generalizable to other domains.

If the task of a study is long, typically many transitions occur leading to a complete transition graph, which is cluttered. For example, to some extent this occurred in the UNO game. One solution is to cut the data into distinct activities [BBB*16]. Too many AOIs are another issue that can occur. If a study has ten or more AOIs, no distinct color can be assigned and the ring sectors would get too small to be distinguishable. An option to overcome this issue is to only show selected AOIs. If a semantic or spatial relation of AOIs is given, another possibility is to depict the parent-AOI of a hierarchical class of AOIs [BKR*16]. Concerning the arrangement of AOIs, in our current version we order the AOIs alphabetically or an analyst can assign them an explicit order. Another possibility is to use a sorting algorithm as discussed in the circular massive sequence approach [vdEHBvW14].

An idea for a future extension could be to either manually or automatically reorder the participants in the *Comparison List View*. An analyst could rearrange the graphs, for example, for the metro map study clustering those graphs that used *transfer 1* and those that used *transfer 2*. This might make it easier to see similarities. An automatic clustering could also be added based on the calculated similarities or other features.

In our expert evaluation, we analyzed data from different types of studies. As shown in Table 2, the first study used static, the second interactive, and the third dynamic stimuli. Therefore, we can conclude that our approach is useful for static as well as dynamic stimuli for finding different eye movement patterns, such as, cyclic viewing behavior, participants using different strategies, or correct or incorrect use of an approach.

Although our approach was developed for the domain of eye movement data in mind, it is also applicable to other domains and data sets. Our approach can be used for movement data in general. For example, one could analyze migration or travel data of individuals where each country a person visited refers to a ring sector and the transitions are the movements from one country to another. Another domain would be the analysis of interactions. When collecting interaction logs during a study with an interactive system, our approach could be used to analyze which views were interacted with and in which order. Similar to eye movement data, the views in an approach could be used as AOIs and mouse movements from one AOI to another could be transitions. In both cases, the data model only needs slight changes.

7. Conclusion

Our primary contribution in this application paper is a visual comparison of transition graphs. Our approach allows an in-detail temporal investigation of transitions. This enables an analyst to find eye movement patterns across participants and for groups of participants as well as outliers efficiently. We evaluated our approach with three experts in two sessions, extending the approach after the first session and re-evaluating it afterwards with the same experts. Overall, the experts made valuable observations about their data. The experts agree that the benefit of the application is to find similar behavior and outliers. Additionally, they mention that our approach is valuable to generate and test hypotheses.

Acknowledgments

We like to thank Markus John, Kuno Kurzhals, and Rudolf Netzel for testing our transition graphs and providing valuable feedback. Fabian Beck is indebted to the Baden-Württemberg Stiftung for the financial support of this research project within the Post-doctoral Fellowship for Leading Early Career Researchers. Metro maps are designed by Robin Woods (www.robinworldwide.com) and licensed from Communicarta Ltd (www.communicarta.com).

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