A Visual Analytic System for Comparing Attention Patterns in Eye-Tracking Data

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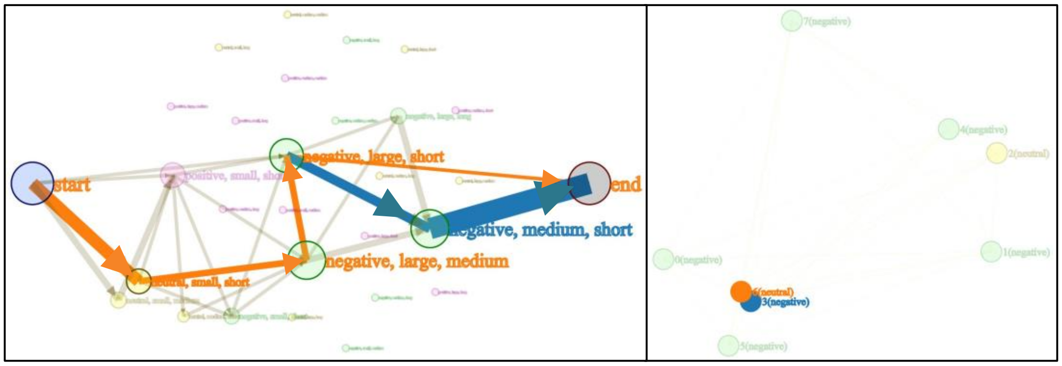

Fig 1. Comparing visual attention patterns using Glyph. The data used for visualization is abstracted from raw eye-tracking data, capturing features of interest such as the size and intended emotion of AOIs, as well as participant's looking time. The left graph shows moment-to-moment pattern, while the right shows overall differences.

Abstract—In this work we present a novel approach of analyzing eye tracking data through temporal analysis of fixation data. We adopt a general visual analytic system called Glyph that facilitates comparison of abstract data sequences to understand group and individual patterns. Using such a system, researchers can understand how users shift in their fixations and dwelling given different stimuli, and how different user groups differ in terms of these temporal eye tracking patterns. In this paper we discuss the system using a case study of eye tracking experiment used to investigate emotion regulation among different age groups through the study of attention to different parts of a video. Temporal patterns for such a study presents a plus on other eye tracking analysis methods.

Index Terms—visualization, eye-tracking data, node-link visualization, eye-tracking data abstraction, glyph

1 Introduction

Eye tracking hardware and software has facilitated research on visual attention and decision-making with implications on marketing and design [1]–[3]. For instance, in the field of psychology, eye tracking has been used to investigate emotion regulation, visual attention, age variation related to attention, etc. [4], [5] Moreover, eye tracking research has been situated in many different environments to tackle different applications, such as advertisement and marketing through looking at visual patterns while watching TV or at a store [6], [7], design through looking at eye patterns while playing games or using a website [8], [9], and automobile design through eye tracking while driving [10], [11], to mention a few. Eye tracking tools for analysis and data capture has been gradually evolving to enable such investigations in a wide variety of uses. In this paper, we specifically target eye tracking data analysis methods.

Typically, researchers who record eye tracking data focus their analyses on aggregations, such as summations of fixations within pre-specified "Areas of Interest" (AOIs) and compare summed fixations toward some AOIs to others, either within or across groups of research participants. Current methods used to aid in this analysis typically visualize eye-tracking data as point-based and AOI-based visualizations [12]. The point-based approach focuses on the movement of fixations and does not require any semantic annotation on the data. In the AOI-based approach researchers annotate the stimuli in terms of areas of interest and visualizations are used to show how fixations are associated such areas of interests, thus giving them meaning and providing context. None of these previous methods have looked at a way to both (a) analyse temporal shifts and patterns of fixation data, and (b) compare these patterns across groups.

In this paper, we propose a novel visual analytic technique for exploration and understanding of look patterns in a 2D, dynamic, active stimulus setup (i.e., video clip watching activity). We developed a coordinated multi-view interactive visualization system, called Glyph, which presents data in two different levels of granularity. Glyph uses an abstract representation of a state transition space represented as a graph to show how each participant has made visual attention choices over time. It coordinates this view with a view that shows how the patterns that users exhibited are either different or similar by having those that are similar close together and those that are different far away. By interacting with the Glyph system, it is expected that users are able to compare attention behaviours, thereby gaining better understanding of participants' choices and how they compare in their patterns. Glyph has been used before to understand player action patterns in video games [13].

For the rest of the paper, we first summarize eye-tracking data visualizations. We then describe our proposed Glyph system. Next, we will discuss a case study where we used Glyph to analyse visual attention patterns among different age groups to understand age differences in attention and emotion regulation. Finally, we discuss some preliminary findings of researchers when using the system, before concluding the work.

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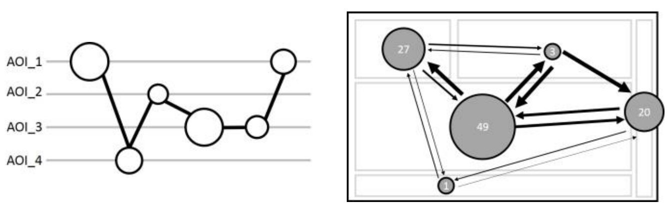
2 RELATED WORK

Frequently used visualization techniques designed for eye-tracking data can be roughly divided into two categories: aggregated plots that disregard temporal information, and those that aim to reflect temporal relationships in the data. The first category includes statistical graphics, such as line, bar charts, scatter/box plots, etc. [14]–[18], and heat maps [19]–[23]. Heat maps are often overlaid on the stimulus as a way to connect the visualized data to its context. The second category comprises of techniques that accumulate eye-tracking data in the visualization without losing temporal information, such as timeline and scan path visualizations [24]–[27]. A thorough categorization of visualization techniques designed for exploratory eye-tracking data analysis can be found in the article by Blascheck et al. [12]. The visualization technique presented in this paper belong to the second category, as we would like to examine attention paths.

In plotting eye-tracking data trails, there are two main approaches: timelines and relational visualizations. In the former approach, time is represented as an axis in the coordination system, such as the x-(horizontal) axis in a 2D space [28], [29], or a third axis in a 3D space [19]. For instance, time plots [28] represents different AOIs as different lines on the y-axis and time on the x-axis, while the node size represent the duration of attention (Figure 2a).

The latter approach on the other hand does not dedicate a specific dimension to time. Instead, it encodes temporal information as transitions between AOI nodes in a node-link representation [30]–[32]. For instance, if the AOIs are represented as nodes, the node size can encode dwelling duration while link thickness depicts the frequency of transition (Figure 2b). More statistical information such as overall dwelling percentage can be displayed as text overlaid on respective nodes. Our visualization as explained in subsequent chapters extends on this approach, i.e., accumulating AOI sequences of participants into a node-link graph. However, in our graph, each node represents an abstract look state, instead of a certain AOI.



(a) time plots (b) relational AOI visualization

Fig 2. AOI-based approaches; (a) time plots with x-axis as time, circle size as duration and y-axis as AOI index/type, (b) relational AOI visualization with AOIs being nodes and links transitions between them. Figures are adapted respectively from [28], [32]

3 GLYPH VISUALIZATION

There are many ways to present eye-tracking data visually to researchers (see Section 2), but in order to make it easy to compare participants and understand the common and unique patterns, we opted for visualizing abstracted data instead of the raw counterparts, using a general data visualization system called Glyph.

The task first requires us to transform raw fixation trails into sequences of *look states*, i.e., abstracted states describing the manner of looking at a specific type of AOIs (e.g., long/medium/short look at a large, positive AOI). Given these abstracted sequences, our goal is to visualize the paths that people in different groups took when watching a specific stimulus over time, such as a video clip. Additionally, we would like the visualization to support the basic exploration acts of (1) identifying common and unique paths, and (2) comparing different paths to one another. Glyph comprises of two coordinated views of sequential behaviour data, showing the state graph and the sequence graph, that work perfectly for this purpose.

3.1 State graph

State graph summarizes the look trails exhibited by all participants. It consists of nodes as look states, and links as transition decisions. For instance, a directed link from a look state characterized by (positive, small, short) to (negative, small, long) means, after quickly looking ("short") at a small-sized AOI ("small") that intendedly elicits positive emotion ("positive"), the participant spends a lot more time ("long") scrutinizing a small-sized AOI ("small") eliciting negativity ("negative"). The popularity of look states, i.e., how frequently the group members land on the state, is depicted by the respective node size. The popularity of transitions is encoded as link thickness. We further use color to depict the affective state of each node: pink is positive, yellow is neutral, and green is negative. The layout of the graph can be force-directed, or clustered according to some prefixed

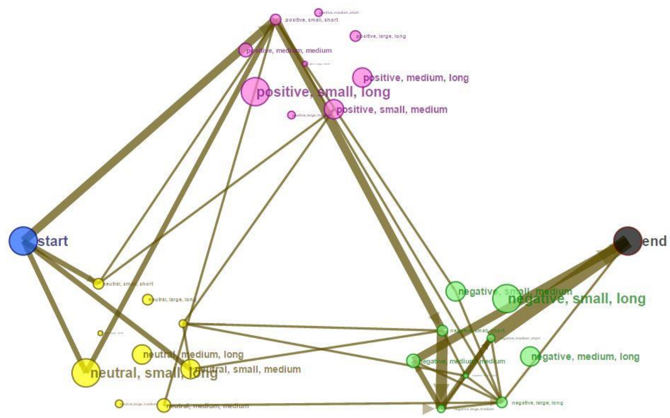


Fig 3. State graph of treatment group data when watching "Marley and Me". Look states associated with positively affective AOIs are pink nodes, neutrally yellow, and negatively green; nodes of the same affective type are clustered in their respective groups. Start (blue) and end (black) nodes do not correspond to any AOI type; they act as landmarks in the graph.

semantic information (Figure 3). The goal of this graph is to allow quick detection of popular transitions, leading to discovery of common group patterns.

Figure 3 depicts an exemplary state graph resulted from visualizing abstracted data obtained from our case study (discussed below) where participants are asked to watch a video clip called "Marley and Me". In this clip, there are four negative, two positive, and two neutral AOIs, as such the majority of the AOIs are negative. Depending on whether participants choose to look at or skip certain AOIs, and how long their eye fixations are in the former case, each participant exhibits a different path from start to end, all of which are collated to form the links and nodes in the graph. Nodes that do not have any links associated with them either (1) denote AOIs that do not exist in the clip, e.g., there is no large positive AOI in "Marley and Me", or (2) represent behaviour not performed by any participant. For example, the graph in Figure 3 shows that nobody spent significant (long) time on small, negative AOIs in this clip. The same applies for links; no link between two nodes indicates that no such transition is present in the data.

3.2 Sequence graph

Different from the state graph, the sequence graph's (see Figure 4) role is to present visually an overview of complete state sequences. Specifically, each node in the sequence graph represents one full pattern, which can be exhibited by one or more participants, the more the larger size it is.

The distances between these sequence nodes are determined using Dynamic Time Warping [33], a method generalizing Minimum Edit Distance [34] to compute sequence differences by accumulating state differences. In general, any metric function deemed suitable to capture

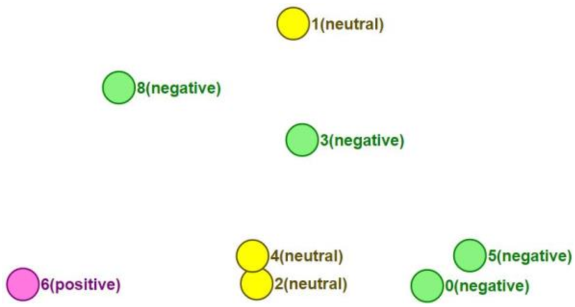


Fig 4. Sequence graph with nodes colored according to the dominant emotion associated with the traced AOIs; yellow nodes are sequences domminated by neutral AOIs, green negative, and pink positive. Node indices indicate popularity.

the difference of abstracted states can be used. Scanpath similarity measures [35] however do not work out of the box, since we need a measure on abstracted data, not the raw scanpath data.

We first define the difference of look states as $d(s_1, s_2) = |V(s_1) - V(s_2)|$, with $V(s_i)$ being the value of the respective look state, computed as:

$$V(s) = \frac{\text{affect}(s) * \text{duration}(s)}{\text{size}(s)}$$

in which

- affect(s) is a numeric representation of the affect associated with the AOI, i.e., -1 for negative, 0 for neutral, and 1 for positive AOIs. Note that this means all neutral look states have value 0, i.e., the look states associated with neutral AOI are not differentiated based on their size or duration, in comparing full sequences. This treatment is eligible, since we are more interested in emotion regulation with respect to positivity/negativity.
- duration(s): the look's duration; short is 1, medium 2, and long 3.
- size(s): the size of the AOI; small is 1, medium 2, and large 3.

The state difference therefore is large if the looks are vastly different, in terms of emotion, size, and look duration. With this metric function, the sequence difference can then be computed using the following procedure.

Dynamic Time Warping: Given $d(s_1, s_2)$ as the difference of any state pair s_1 and s_2, the difference $D(a, b)$ of two sequences $a = \{s_1, s_2, \ldots, s_n\}$ and $b = \{q_1, q_2, \ldots, q_m\}$ is computed as $D(n, m)$ as follows

1. Initialization:
   a. $D(0,0) = 0$
   b. For i in $[1, n]$ and j in $[1, m]$: $D(i, 0) = D(0, j) = inf$
2. Recursion: For $i = 1$ to n and $j = 1$ to m

$$D(i,j) = d(s_i, q_j) + min\begin{bmatrix} D(i-1,j), \\ D(i,j-1), \\ D(i-1,j-1) \end{bmatrix}$$

3. Return $D(n, m)$

3.3 Visual Coordination: Synchronized Highlighting

The two graphs in Glyph are coordinated through the use of synchronized sequence highlighting, in which the selection of a sequence node will at the same time highlight the rolled out representation in the state graph (Figure 5). This allows easy comparison at two levels of details: moment-to-moment in the state graph, and full sequence difference in the sequence graph.

The coupling of state and sequence graphs through visual coordination facilitates three important cognition tasks:

1. *Detection of attentional patterns:* The sequence graph allows quick detection of common patterns, recognized as groups of sequence nodes in close proximity. By selecting a group of similar nodes, users can examine all fixations and states involved in the state graph to come up with hypotheses about this group's behaviour.

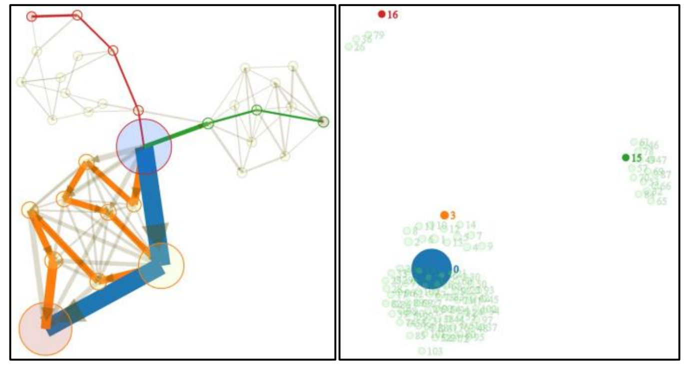


Fig 5. Coordinated highlighting: selection of sequence nodes in sequence graph (right) highlights respective paths in the state graph (left) with the same colour.

2. *Detection of unique behaviour*: Isolated nodes in the sequence graph represent paths that are significantly different from the population. Examining corresponding paths in the state graph helps user gain insights on what happened and thus hypothesize on why.
3. *Comparison of behaviour*: Examining vastly different or similar paths (shown as nodes far apart or close by in the sequence graph) in the state graph allows users to understand the nuanced differences between them.

4 Case Study

To apply the visualization system and show its utility in opening up different methods of analysis, we teamed up with a psychology group who is running a study on visual attention, emotion regulation and differences between age groups. In this project, the researchers aimed to investigate the effect of age on use of certain emotion regulation strategies. Previous research indicates a positivity bias on the part of older adults when compared to younger and middle aged adults. This means that, in general, older adults report being happier than their younger counterparts, and also tend to focus their attention and memory on positive rather than negative material [36]. Eye tracking can be used to determine whether there is an age difference in how individuals modulated their attention based on how they feel [5]. As such, the overall research question for the study was: *how do adults of different ages use affective choices and visual fixation to regulate negative mood states?*

4.1 The Study

In order to answer the above question, the researchers designed an experiment, in which participants are tasked to choose from a variety of clips that can cause positive and negative emotions to watch. For instance, a clip selected comes from the last scenes of the movie "Marley and Me", showing memories the main character had with his dog while facing the fact that the pet is dying soon. While the memories generally contain fond and happy moments, the up-close shots of the dying dog could cause great sadness to viewers.

Initially 150 subjects were recruited. After filtering (i.e., only include participants with gazes tracked at least 75% of the time), there are a total of 42 young adults (18-34yos, μ=20.52, σ=1.58), 45 middle-aged (35-64yos, μ=48.2, σ=6.73) and 45 old adults (≥65yos, μ=70.85, σ=7.35) in the data set. They are further divided into two groups: the treatment group (65) are asked to stay positive throughout the session of clip watching, while the control group (67) are not given any instruction. Because participants can select which clips to watch, not every participant in the study watched the same clips. Each participant watches the clips alone to avoid any noise caused from group interaction. The gaze points of participants throughout the session are recorded, showing where they look at, when, and for how long.

The researchers are specifically interested in understanding how participants deploy their attention, with instruction and age being two controlling variables that affect their attention patterns; the collected data is being actively studied. Visualizing the data using Glyph aims at allowing them to identify commonalities as well as uniqueness in eye-gazing behaviour. The visualization examples shown in Figure 6 were from one particular clip, i.e., the "Marley and Me" clip as described above. While not all participants watched this clip; there are about 16% of them did (9 treatment, and 8 control).

4.2 Data Preparation

The clip that participants watch is annotated a priori with AOIs, marked up as "positive", "negative", and "neutral". While positive and negative AOIs are those that presumably cause watchers to experience respective emotions, neutral AOIs are visually interesting by themselves but do not carry any emotion meaning. For each AOI, we know where and how much screen estate it takes up within the frames where it appears, as well as how long it lasts.

Participant eye fixation data was recorded at a temporal resolution of 30 Hz, and an accuracy of .050-1.00 visual angle using an ASL (Applied Science Laboratories, Bedford, MA) MobileEye XG eye-tracker. Fixations were defined in the system as holding a point of gaze for 100ms without deviating more than one visual degree. As such the fixation data details with high accuracy where the participants look at and when.

Given AOI information, we could abstract the raw data, turning them into sequences of *look states*, each of which consists of three descriptors

1. The emotion associated with the AOI: negative, positive, or neutral. Negative AOIs contain unpleasant scenes (e.g., a dying dog), while positive ones contain visuals that are uplifting or pleasant to view (e.g., a dog playing cheerfully with the owner in the back yard). Neutral AOIs on the other hand consist of visually salient objects, which naturally draw the viewers' attention but do not aim at any specific emotion (e.g., an untidy room with objects of different sizes and types scattering around).
2. The size of the AOI: small, medium, or large. A small AOI covers less than 25% of the screen during in its duration, medium 25-49.99% of the screen, and large greater than 50%.
3. The duration of looking, i.e., short, medium, or long. This attribute is computed in comparison to the total duration of the AOI. A short look only lasts less than one third of the total duration, medium 1/3-2/3, and large greater than 2/3.

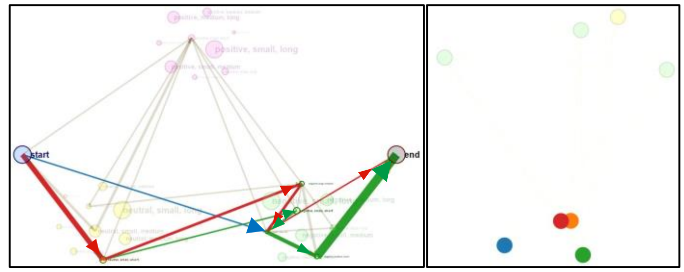
Each participant's eye-track log is processed in this way over the course of the clip's duration, to return a sequence of look states.

5 Discussion

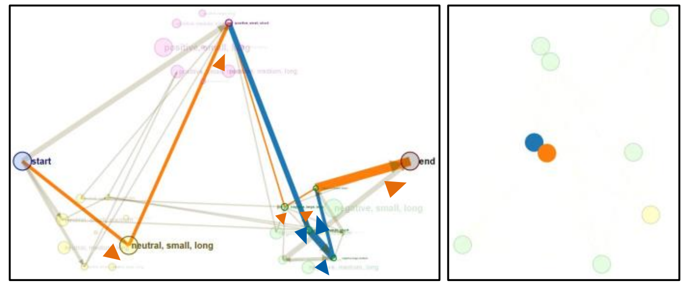
As reported by the researchers, the visualization's most useful feature was the ability to highlight common routes through the video, thereby showing similarity between participants. This feature of the tool is currently used to study differences among subject age and treatment groups in terms of within-group common visual routes. For example, Figure 6 shows the behavior differences in the two groups, suggesting that the treatment group (i.e., instructed to stay happy) seems to put in some effort to stay happy as their popular trails pass by positive AOIs more often (Figure 6b), whereas the control group (i.e., without any instruction) does not attempt to do so, i.e., popular trails did not include nodes associated with positive AOIs (Figure 6a).

Having tried Glyph, the researchers learnt that this system would benefit from a slightly altered experiment setup. Currently, the clips used in our study are composed of segments of one single emotion (i.e., the choices are vertical). For instance, "Marley and Me" shows segments of positive, neutral, or negative emotion but not all of them at a time. Therefore, participants do not have a complete freedom in selecting what they want to watch. They can only choose to pay more, less, or none at all, attention at each frame. Ideally, if we have clips that comprise of more emotions mixed together within a single frame or segment, subjects will be granted more freedom in selecting the region of interest at any point of time. For example, if a scene shows at the same time a sad event in one corner of the screen and a happy event in the other, tracking the eye movement of the subject will better inform us about their choices, i.e., whether the subject focuses more on the happy area or the sad area in that clip segment. In such case, the tool would help researchers understand subjects' decisions in the context of multiple alternatives, i.e., horizontally.

Future work would entail more analysis with the current system and utilizing it more in the analysis process within psychological experiments (the described study is still ongoing). We also aim to integrate this system within other eye tracking experiments to see how well it generalizes and also develop it for better flexibility to allow best utility given the divergent eye tracking research questions.



(a) Control group



(a) Treatment group

Fig. 6. Most popular strategies highlighted in two subject groups. The state graph is laid out so that nodes associated with positive AOIs are in the top cluster, neutral bottom left, and negative bottom right. (a) Control group's most popular trails do not visit nodes in positive AOIs (), while (b) treatment group's most popular trails do. Note that currently overlapped links take colors of one of the selected trails.

6 Conclusion

In this paper, we proposed a novel approach in analysing eye tracking data using a visualization system we developed called Glyph. The process includes an abstraction phase where raw eye fixation data are projected into an abstract state space. Next, the data is visualized in two graph views, namely state and sequence graphs, which display the data in two forms: state sequences and aggregated representations. Using coordinated highlighting to synchronize the content presented, the final system aims to facilitate user interactions to complete three cognitive tasks: detection of attentional patterns, detection of unique behaviour, and comparing behaviour sequences. The preliminary assessment of the system with the researchers demonstrated the prospect of the system. As this proposed method is still in its infancy state, we hope to continue developing it in many eye-tracking experiments and would welcome more studies trying this approach to examine temporal patterns of attention.

Acknowledgments

This work was supported in part by NIA grant R21 AG044961.

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