Eye Fixation Metrics for Large Scale Analysis of Information Visualizations

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(a) ORIGINAL (b) SCAN PATH (c) DURATION PLOT (d) FIXATION HEATMAP (e) COVERAGE PLOT

Fig. 1. We present multiple ways of analyzing and visualizing eye movements on information visualizations: (a) original image, (b) scan path (ordered eye fixations), (c) duration plot, where each fixation is plotted of size proportional to its duration, (d) fixation heatmap - a density plot of the regions most fixated, and (e) coverage plot, highlighting the image area covered by fixations. These different visualization modalities can uncover different aspects of how observers examine information visualizations.

Abstract—An observer's eye movements are often informative about how the observer interacts with and processes a visual stimulus. Here, we are specifically interested in what eye movements reveal about how the content of information visualizations is processed. Conversely, by pooling over many observers' worth of eye movements, what can we learn about the general effectiveness of different visualizations and the underlying design principles employed? The contribution of this paper is to consider these questions at a large data scale, with thousands of eye fixations on hundreds of diverse information visualizations. We survey existing methods and metrics for collective eye movement analysis, and consider what each can tell us about the overall effectiveness of different information visualizations and designs at this large data scale. We also discuss techniques to visualize some of the properties of fixation behavior that our eye movement metrics aim to capture.

Index Terms—Information visualization, eye-tracking study, fixations, metrics, methodology

1 INTRODUCTION

Eye movements can provide us with clues about the elements of a visual display that people pay attention to, what they spend most time on, and how they redirect their attention between elements. The eyes can also be used as indicators of higher-level cognitive processing, like memory, comprehension, and problem solving [16, 17, 24, 26, 27, 39].

There is a significant body of existing literature with eye movement analyses on natural scenes, simple artificial stimuli, webpages, user interfaces, and increasingly, information visualizations. In the visualization community, eye-tracking analyses have been used to independently evaluate different visualization types (graphs [19, 20, 21, 26, 34], tree diagrams [6], parallel coordinates [44]) and to directly compare visualization types [4, 7, 12]. Eye-tracking has also been used to understand how a person visually perceives, explores, searches, and remembers a visualization, providing a window into the cognitive processes involved when interacting with visualizations [1, 2, 4, 7, 20, 25, 34, 35, 38]. In human-computer interaction (HCI), eye-tracking analyses have often been used for evaluating the usability of systems and studying the related question of interface design [9, 14, 22, 32].

Depending on the analysis, different aspects of oculomotor behavior are measured, including standard metrics like mean fixation duration [24], saccade rates[1], gazing time [22, 32, 36], fixations per area of interest [12, 37], etc. **Fixations** are discrete samples of where an eye was looking on a visual display obtained from continuous eye movement data. Many fixation metrics, however, can be summarized by a few main properties, including fixation locations and durations, temporal ordering (sequence) of fixations or **scan path** [31], and fixation coverage or density (proportion of the visual input fixated). Different types of visualizations and visualization tools for examining properties of eye movement data have been useful for complementing and facilitating analysis over groups of observers [1, 13, 28, 41, 46, 47, 49, 50].

In this paper, we review existing eye fixation metrics in the context of a large dataset of information visualizations and eye movements. This large data setting allows us to consider metrics suitable for the comparison and evaluation of visualization designs, by accumulating statistics over a population of observers. Unlike many previous studies, our analyses are broad, spanning a large diversity of visualization types and sources. We discuss and visualize ways in which different metrics can be used to evaluate the effectiveness of different visual-

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[1]Saccades are intervals between fixations: the motion of the eyes from one fixation point to the next. The analysis of saccades is beyond the scope of the present paper, for which additional metrics would be necessary [27, 36].

ization designs, and we use the MASSVIS dataset [4] to provide some specific examples. The review provided in this paper is intended to motivate further research into large-scale eye movement analysis for the broad comparison and evaluation of visualization designs.

2 Methods

2.1 Visualization data

We used the MASSVIS dataset of 393 labeled target visualizations, spanning four different **source categories**: government and world organizations, news media, infographics, and scientific publications [4]. These visualizations were manually labeled by three visualization experts using the LabelMe system [42] and Borkin et al.'s visualization taxonomy [5]. The labels classify **visualization elements** as: data encoding, data-related components (e.g., axes, annotations, legends), textual elements (e.g., title, axis labels, paragraphs), pictograms or human recognizable objects (**HRO**), or graphical elements with no data encoding function. Labels are available as segmented polygons.

2.2 Eyetracking experiments

We used the eye movements from the MASSVIS dataset, collected during the *encoding* experimental phase [4]. Eye movements of 33 participants were recorded on 393 visualizations, with an average of 16.7 viewers (SD: 1.98) per visualization. Equipment included an SR Research EyeLink1000 desktop eye-tracker [45] with a chin-rest mount 22 inches from a 19 inch CRT monitor (1280 x 1024 pixels). Each visualization was shown to participants for 10 seconds, producing an average of 37.4 (SD: 6.6) eye fixations per viewer per visualization, or an average 623 (SD: 93) total fixations per visualization.

3 Metrics and Visualizations

For each eye fixation, we record its spatial location in pixel coordinates, duration in milliseconds, and ordering within the entire viewing period (scan path). Visualizations like the ones in Fig. 1 make it easier to qualitatively explore patterns in the eye movement data. We plot the fixations an observer makes on an information visualization, using either the fixation ordering (for a scan path visualization, Fig. 1b) or duration (for a duration plot, Fig. 1c) as a visual marker. The color of the marker reflects the recency of the corresponding fixation in the viewing period. In the scan path visualization each marker is additionally numbered according to the fixation ordering, while in the duration plot each marker is sized proportionally to the duration of the fixation. We can also generate a **fixation heatmap** from the fixations of a single observer or a group of observers by placing a Gaussian[3] at each fixation location. The result is a continuous distribution that can be plotted on top of the image to highlight elements receiving the most attention.

Different visualizations of fixation data emphasize different aspects of eye movement behavior, which in turn link to different underlying cognitive processes. For instance, the number or density of fixations allocated to a visual area has been linked to its importance; fixation duration in a visual area to the area's information content or complexity; and the transitions between fixations to the search behavior and expectations of the viewer [11, 29, 39]. Patterns in the fixation data of a group of observers can also be used to highlight design features or diagnose potential problems. For instance, the order of fixations has been linked to the efficiency of the arrangement of visual elements [11].

To complement qualitative trends that emerge from the visualizations of the fixation data, the quantitative metrics presented below can be used to summarize the eye movement behavior of a population of observers on different collections of information visualizations.

3.1 Fixation Measurements

To quantify fixation behavior, eye tracking studies typically consider measurements like the number and distribution of fixations. These types of statistics can be used to make inferences about observer engagement, for instance. Across the MASSVIS visualizations, scientific visualizations received the fewest fixations (M=34.6, SD=3.1), statistically significant from other sources; and news visualizations received the most fixations (M=39.04, SD=2.6), also statistically significant at the $p = 0.05$ level under Bonferonni-corrected t-tests. We can use this metric to hypothesize that observers were more engaged by the news visualizations, but need additional user studies for validation.

Having labeled (pre-segmented) visualization elements[4] allows statistics to be accumulated over observers and visualizations, to relate eye movement behavior back to these elements. Table 1 lists the fixation metrics we compute. For instance, instead of asking how many fixations are made on a visualization, with labeled visualization elements we can ask how many unique elements are fixated (which we denote **DOF**, or "diversity of fixations"). Note, however, that this analysis is most meaningful when multiple visualizations have a comparable number of elements. In MASSVIS, the infographic and government visualizations have the largest and smallest DOF values, respectively, but the infographic visualizations have on average over three times as many visualization elements as do government visualizations.

When differentiating between collections of visualizations (e.g., from different source categories) is not meaningful, fixation statistics can be collapsed over all visualizations to make conclusions about general design principles. For example, by accumulating fixations over observers and visualizations in the MASSVIS dataset, we find that titles, labels, and paragraphs are the elements most often fixated when present. Across infographics, the title is fixated 72% of the time across all observers. When a title is not present, observers look to any other explanatory text (e.g. paragraph, legend, or annotations). This trend is also visible in the fixation heatmaps (e.g., Fig. 1d).

An analysis of scan paths can indicate which elements are fixated first and which elements are fixated multiple times (**refixated**) during the entire viewing period. This can in turn provide a measurement of relative element importance. Across MASSVIS visualizations, the elements often fixated first are annotations, titles, and paragraphs - i.e. textual elements from which an observer can expect to learn the most about what the visualization is conveying. The legend, not surprisingly, is the element refixated the most often (Fig. 3), since it allows the information in a visualization to be clarified and integrated.

Total fixation time (**TFT**) and corresponding duration plots can be used to complement statistics about the number and distribution of fixations. In the MASSVIS dataset, low TFT numbers indicate that observers tend not to dwell on pictograms (HRO) and purely-visual elements, and instead spend most of the time reading text (Fig. 3). This supports previous findings that viewers start by visiting, and spend more time on, textual elements than pictorial elements [40]. This does not mean that observers do not look at pictograms. On the contrary, almost as many fixations are allocated to HRO as to key text elements, like the title and paragraphs (Fig. 3). However, fixations on these elements do not last as long: observers look at these elements, and move on. Thus, considering a number of different fixation metrics concurrently paints a clearer picture of observer eye movement behavior.

3.2 Coverage

Coverage, closely related to spatial density metrics [8, 14], measures the amount of image area covered by fixations [49]. In other words, how much of the visualization did observers actually look at? Coverage is computed by thresholding the fixation heatmap at some fixed threshold[5] across all of the visualizations to facilitate comparison. Low coverage indicates that only a small portion of the image was

[2] We use the standard thresholds set by the EyeLink Eyetracker [45].

[3] Typically, the sigma of the Gaussian is chosen to be equal to 1 or 2 degrees of visual angle, to model the uncertainty in viewing location.

[4] In eye tracking literature, segmented image regions for quantifying eye movement behavior are called Areas of Interest (AOIs) or Regions of Interest (ROIs). Goldberg and Helfman [12] discuss implementation choices and issues arising when working with AOIs and fixations.

[5] We chose a threshold of 0.1 on normalized maps by empirically observing that it helped visually differentiate between visualizations. This threshold depends on the parameters of the Gaussian used to create the fixation map. Additionally, coverage is also a function of time. Given a very long time to look at a visualization, there is no reason why there would not be full coverage.

Table 1. Eye-tracking fixation metrics calculated in order to evaluate the results of participants' encoding and recognition gaze patterns.

MEASURE	DESCRIPTION
Fixations	Fixations are discrete sample extracted from eye movement data. A fixation is recorded when the eyes are "still" according to prespecified parameters[2][43, 18].
Refixations	The number of times a viewer returns to an element during the entire viewing period (including the first time the element is fixated). Consecutive fixations on the same element are not counted.
Total fixation time (TFT)	Total duration of a viewer's fixations landing on a given visual element throughout the entire viewing period.
Fixation time per unit area (FTA)	A viewer's total fixation time (TFT) divided by the area (in pixels) of a visual element.
Diversity of fixations (DOF)	The number of unique elements fixated upon by a viewer during the entire viewing period.
Inter-element fixations (IEF)	The number of times a viewer fixates on a different set of visual elements from one fixation to the next. Some of the elements fixated can be the same, as long as the whole set is different.

actually fixated. Analyzing coverage can help diagnose potential design issues. If a large part of the visualization is covered in data but fixation coverage is low, then observers may have missed crucial parts of the message. Consider the examples in Fig. 4: an analysis of coverage can tell us which components of each visualization may have been missed by observers. Overall, among the 50 visualizations with highest coverage in the MASSVIS dataset, 34% are infographics, while of the 50 visualizations with lowest coverage, 40% are news media. Infographics visualizations have on average more coverage (0.44) than news media visualizations (0.40, $p < 0.05$). Recall that the news media visualizations received the most total number of fixations. Does this contradict the coverage finding? Both infographics and news media visualizations receive the most fixations, indicating high observer engagement, but our news media visualizations tend to be simpler and have fewer components than our infographics. As a result, fixations on the news media visualizations are more clustered around a few components, leading to lower coverage. Again, by considering multiple fixation metrics, a fuller story unfolds.

3.3 Inter-Observer Consistency

Inter-observer consistency (**IOC**) is used in saliency research[6] to quantify the similarity of observer fixation patterns on an image. IOC for an image is a measure of how similar the fixation heatmap using N-1 observers is to the fixation heatmap of the remaining observer, averaging over all N observers, under some similarity metric[7]. We propose that IOC analysis can be used to determine how the design of an information visualization guides observers. High IOC implies that observers tend to have similar fixation patterns, while a low IOC corresponds to different observers examining a visualization in different ways. In the latter case, it is worth measuring if the different possible fixation patterns will lead observers to derive similar conclusions from the visualization. Will the message of the visualization be clear no matter how the visualization is examined? Did the designer of the visualization intend the visualization to be viewed in a particular way? A low IOC is a sign that not all observers may be examining the visualization as intended. Fig. 2 contains example fixation heatmaps for a visualization with low IOC and one with high IOC. In general, dense and crowded visualizations with a lot of information have low IOC; there is a lot to look at, and different observers choose to look at different things. Simple, clean visualizations direct the observer's attention, and as a result different observers look at these visualizations in similar ways.

3.4 Fixation durations

Different fixation durations have significance in the psychology literature. For instance, shorter-duration fixations, less than about 200-250 ms, are sometimes considered involuntary (the eyes move there without a conscious decision) [15]. Fixations less than about 300 ms are thought not to be encoded in memory. By plotting heatmaps of fixations at various durations in Fig. 5, we can see which elements of a visualization are explored for shorter or longer periods of time, and thus potentially differently processed. Durations of fixations have

Fig. 2. **Top row:** a visualization with low inter-observer consistency (IOC). Different observers examine the visualization in different ways but will they get the same information out of it? **Bottom row:** a visualization with high IOC. All observers have a very similar fixation pattern on this visualization. This visualization tends to consistently guide the observer's attention. For ease of comparing the fixation patterns of different observers, the underlying visualizations have been gray-scaled.

been found to be related to the complexity and difficulty of the visual content and task being performed [11, 33, 39]. Thus, considering locations in a visualization receiving fixations of increased duration could be used to diagnose more difficult-to-process components, or elements of the visualization that are engaging the cognitive resources of the observer. For instance, across the MASSVIS visualizations, observers dwell for longer periods of time on the actual data content, rather than just the explanatory text, indicating that they are engaged by the data and the text alone may not suffice.

4 Conclusion

In this paper we have reviewed a number of existing eye movement metrics and considered their utility for the collective analysis of large, diverse datasets of visualizations. By accumulating statistics over observers and visualizations, these metrics can be used to quantitatively evaluate different types and designs of visualizations. We also discussed a number of techniques for visualizing some properties of fixation behavior that these metrics aim to capture[8]. The contribution of this paper was to consider broader, more large-scale comparisons than prior studies in the visualization community.

There remain many opportunities for applying additional eye movement metrics and visualization techniques to large-scale datasets of information visualizations, to drive quantitative comparisons between designs, and to derive general design principles. Whereas in this paper we focused mostly on the distribution of fixations, the investigation of other properties of eye movement behavior like scan paths and saccades are likely to provide additional insights. The results of eye movement analyses have the potential to make simultaneous contributions to the understanding of human cognitive and perceptual processes, visual content design principles, and general approaches to data communication.

[6]This has also been called inter-subject consistency [48], the inter-observer (IO) model [3], and inter-observer congruency (IOC) [30].

[7]Area Under Receiver Operating Characteristic Curve (AUC) is the most commonly used similarity metric [10]. Note that IOC analysis can be extended to the ordering, instead of just the distribution, of fixations [13, 23, 30, 31].

[8]Labeled visualizations, eye movement data, and the visualization tools presented in this paper will be made available at `http://massvis.mit.edu`.

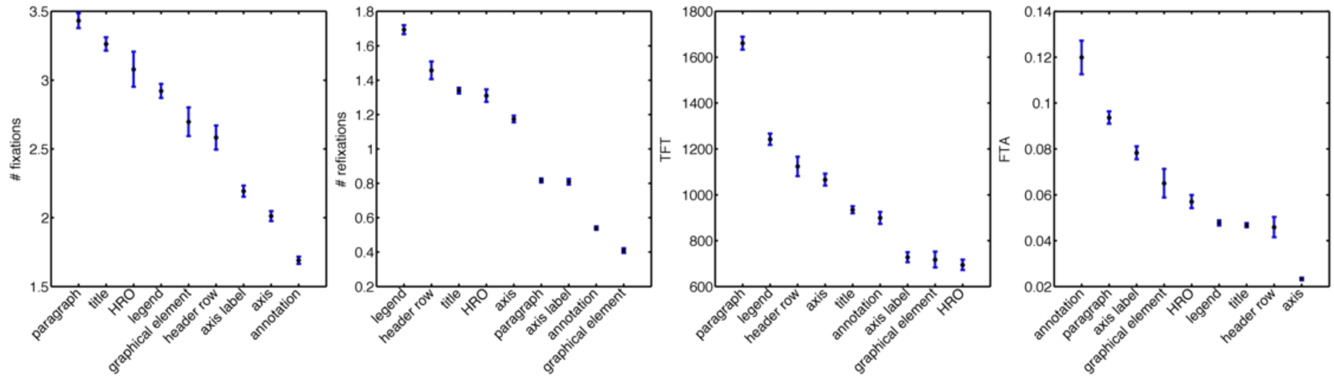

Fig. 3. Each plot includes a fixation metric (see Table 1) computed by intersecting fixation locations of observers on information visualizations with polygons outlining the visualization elements. The visualization elements are listed on the x-axis of each of these plots. The values plotted are means and standard errors computed over all the observers and all 393 target visualizations. We can see that textual elements tend to receive the most attention during viewing of information visualizations.

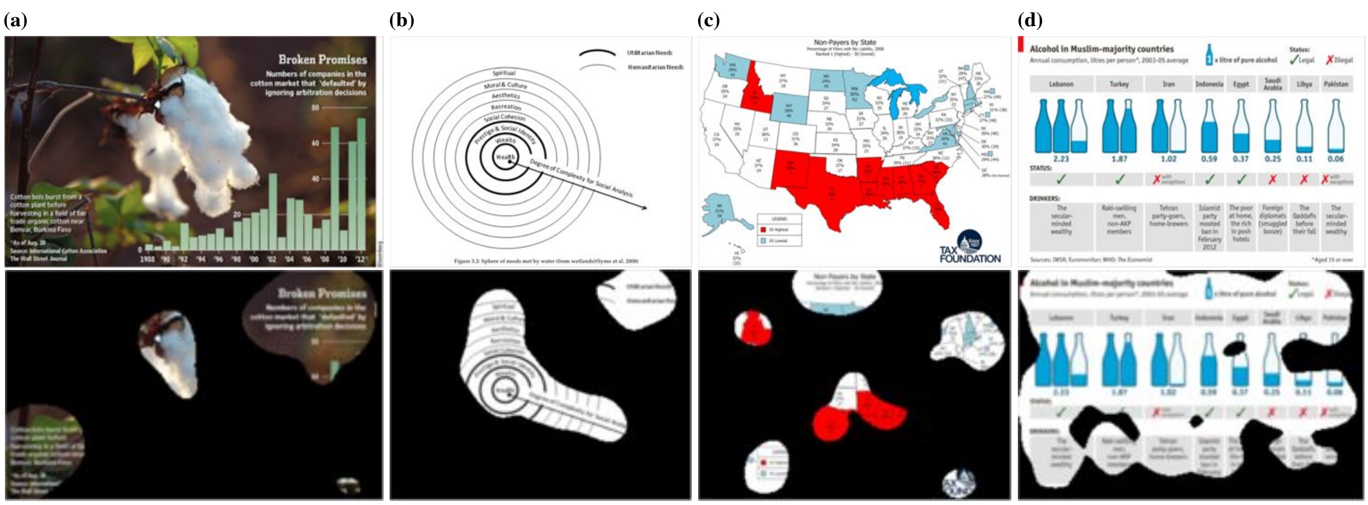

Fig. 4. Analyzing fixation coverage can help diagnose potential design issues. (a) The photographic element may have distracted observers, who paid no attention to the bar graph; (b) The title at the bottom, explaining the visualization, was missed; (c) Some regions of the map attracted observers' attention more than others, and the logo at the bottom right redirected attention; (d) A visualization with many components and high coverage - observers were engaged, and examined the majority of the visualization.

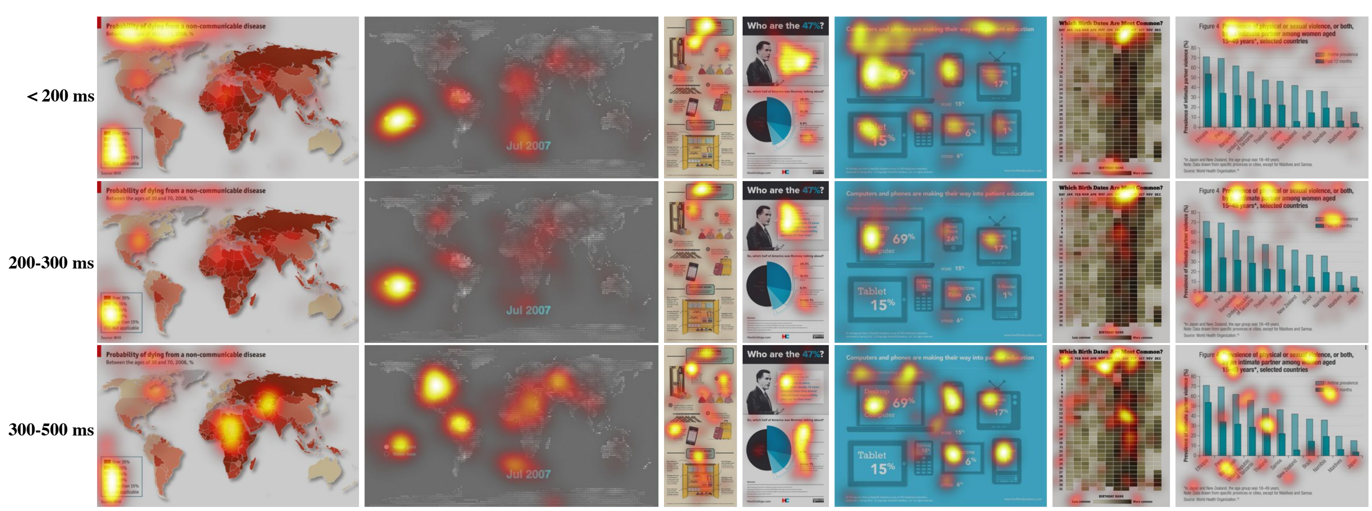

Fig. 5. Heatmaps created by selectively accumulating fixations of different durations, across all observers. **Top row:** fixations less than 200 ms. **Middle row:** fixations between 200 and 300 ms. **Bottom row:** fixations between 300 and 500 ms. Here we see that longer-duration fixations are used to explore more of the data elements. Fixation durations are linked to the complexity and informativeness of a visual area.

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