The Role of Eye Tracking in Adaptive Information Visualization

Anna Flag,Mona Haraty,Guiseppe Carenini,Cristina Conati
Department of Computer Science, University of British Columbia
2366 Main Mall, Vancouver, BC
aflagg,haraty,carenini,conati@cs.ubc.ca

ABSTRACT
We plan to design adaptive information visualization systems that adjust to the specific needs of each individual viewer. Our first step is to explore data sources that could help predict different levels of performance on visualization tasks, including interface interactions, eye-tracking, and physiological sensors. In this poster, we discuss how a viewer's gaze pattern could inform the design of adaptive visualization systems.

Author Keywords
Gaze, information visualization, adaptive user interface, individual differences, eye tracker.

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Information visualization is a thriving area of research in the study of human/computer communication. However, attempts to measure and formalize visualization effectiveness often have led to inconclusive and conflicting results [14]. We believe this is because existing visualizations are designed mostly around the target data set and associated task model, with little consideration for individual differences. Both long term traits like cognitive abilities and short term factors like mental state have been largely overlooked in the design of information visualization systems, despite studies linking individual differences to visualization efficacy for search and navigation tasks [1,7], as well as anecdotal evidence of diverse personal visualization preferences [3]. Thus we plan to explore the possibilities of intelligent, human-centered visualizations that *understand* different users have different visualization needs and abilities, and can *adapt* to these differences.

There is already some evidence of the impact individual differences can have on visualization effectiveness. For example, Velez, Silver, and Tremaine [15] found significant correlations between individual spatial abilities and performance on identification of a 3D object from visualizations of its orthogonal projections. Conati and Maclaren [5] found that an individual's perceptual speed was a significant predictor of her ease in understanding the same data set with two different visualization types.

Although the benefits of user-adaptive interaction have been shown in a variety of tasks such as operation of menu-based interfaces, web browsing, desktop assistance and human-learning [10], these ideas have rarely been applied to data visualization. This is largely due to the fact that there is limited understanding of which combinations of user traits/goals are relevant for adaptivity. Two notable exceptions are the work by Gotz and Wen [8], and by Busilowsky et al. [4].

Gotz and Wen [8] propose a technique to automatically detect a user's changing goals during interaction with a multi-purpose visualization, and adapt the visualization accordingly. In contrast, we focus on adapting the visualizations to other relevant user-dependent factors in addition to goals. Brusilowsky et al. [4] adapt the *content* of the visualization to the user's state in an educational system, but maintain a fixed visualization technique. In contrast, we are interested in adaptation that involves both selecting *alternative visualizations* for different users, as well as providing *adaptive help* with a given visualization to accommodate changing user needs during interaction.

To achieve this objective, two research questions need to be answered: 1) given a visualization, why do some people perform better than others, and 2) how can a visualization system detect when a user is not performing well. We plan to explore two avenues to answer these questions. One is to investigate further how long term user traits (e.g, spatial/perceptual abilities, personality traits, learning styles) may impact visualization effectiveness. If such measurable features are found and are collectible before interaction, they could be given as input to the system to help it select the best visualization method for this viewer. Our second approach is to study whether user proficiency with a given visualization can be inferred from her interaction behaviors. We believe that an important window into these behaviors can be provided by eye-tracking information. The rest of the paper focuses on some preliminary ideas on how this information can be collected and utilized in the design of adaptive visualizations.

GAZE PATTERN: AN INPUT TO ADAPTIVE VISUALIZATIONS
Several researchers have explored eye-tracking as a source of information for real-time assessment of human/machine interaction performance. Amershi and Conati [2] used an

unsupervised machine learning technique to separate effective and ineffective user behaviors during interaction with a teaching tool for math. The behaviors captured both interface actions as well as attention patterns monitored via eye-tracking. We plan to conduct similar studies to try to reproduce these results in the context of visualizations.

Iqbal and Bailey [9] found that a given task, including a reading comprehension, searching, or object manipulation, has a unique signature of eye movement. We hypothesize that the correlation between task performance and a specific class of gaze patterns might depend on the type of visualization being used. To test this hypothesis, we will analyze several visualizations such as bar graph, line plot and pie chart for a specific task. For example, users will be asked to perform the following filtering task: "Find data cases satisfying the following concrete conditions on attribute values.". We will monitor the resulting interactions and see if we can identify common "successful" gaze patterns for each visualization.

We believe the following results can help us model user performance on a visualization using gaze behavior:

1. The duration of fixations on each area of interest is an indicator of the complexity of that area [6,11]

A study by Crowe and Narayanan found that-as one might expect-an unusually long fixation on one component of a visualization indicates lack of understanding of that component [6]. Identifying these areas may make for a more focused adaptation, because it allows the system to target the specific area that is perplexing the viewer.

2. Degree of pupil dilation has been proved to be a valid and reliable measure of cognitive load [12]

We plan to investigate if pupil dilation as measured via an eye-tracker can be a reliable indication of cognitive load during visualization processing. If this is the case, detecting high cognitive load could prompt the system to take steps to simplify the data presentation or the viewer's task.

3. Users do not look at all areas of interest [9,13]

Analyzing gaze locations might be a good first step to identifying when a viewer is having trouble with a given visualization. Lohmann, et al. used this approach to compare relative effectiveness of alternative tag cloud visualizations in the context of drawing attention to the areas of greatest interest [13]. Gaze locations, and the locations that have been overlooked, can inform the design of the adaptive help. For instance, after becoming aware the viewer is not looking at an area of crucial importance, the visualization could emphasize this area to attract attention.

UTILIZING GAZE DATA FOR TWO TYPES OF ADAPTATION

We are interested in adaptation that involves both selecting different visualizations for different viewers, as well as providing adaptive help within a visualization to accommodate changing user needs during interaction. For example, given a set of alternative visualizations, our adaptive system would monitor the interaction and may switch visualizations if the current display does not appear to be working for the viewer. During the interaction itself, the system would focus more on providing explicit interactive help, such as drawing attention to certain important areas or explaining explicitly how to derive a given piece of information from the current visualization.

These proposals for adaptation must be thoroughly tested within the context of information visualization before they can be realistically applied. Thus, in addition to conducting studies to validate the use of eye-tracking data in detecting when a viewer is having difficulties, we plan to investigate the benefits and feasibility of a variety of adaptive interventions within the context of information visualizations.

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