Expanding the Porthole: Leveraging Large, High-Resolution Displays in Exploratory Visual Analysis

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Abstract

The scale and complexity of today's datasets frequently overwhelms conventional visualization interfaces, which could negatively impact the quality of the visual analytic activity. In this paper, we investigate the use of Large, High-Resolution displays in exploratory visual analysis scenarios. We argue that the ability to see and interact with more information at once fundamentally affects users' analytic behavior, prompting them to explore their data more broadly. This positive effect may also enhance the diversity of questions and hypotheses conceived and explored by users during their analysis.

Author Keywords

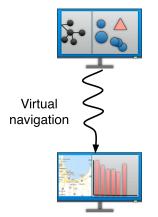
Information visualization; visual exploration; visual analytics; large high-resolution displays.

ACM Classification Keywords

H.5.2. Information interfaces and presentation (e.g., HCI): Graphical user interfaces (GUI).

Introduction

Exploratory data analysis paradigms emphasize the use of interactive visualization tools to explore and make sense of large amounts of information. This approach favors a broad inquiry with the goal of generating



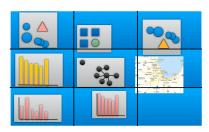


Figure 1. Compared to conventional monitors, *large*, *high-resolution displays* make it possible to display multiple information views side-by-side at sufficient levels of detail. This enables users to see a larger portion of the information space at once and reduces the need for virtual navigation (such as pan and zoom, or window switching). plenty of meaningful questions about the data. Accordingly, an important quality indicator in exploratory analyses is the diversity of questions considered, as reflect by the formulation of multiple competing hypotheses and the analyst's attempt to look at the data from different perspectives [1]. Interactive visualization tools can foster such exploratory qualities by affording interactions that enable users to navigate large datasets and explore relationships between different components of the information space. However, as data grow in size and complexity, attaining breadth and diversity becomes more difficult.

Tiny portholes

Most users interact with visualizations using conventional desktop and laptop displays, which provide limited screen space and resolution. When the information space is large, virtual navigation techniques, such as pan+zoom and overview+detail interfaces become necessary to allow the user to navigate the space. However, virtual navigation comes with significant temporal and cognitive costs, requiring the user to spend time and effort moving back and forth between different parts of the information space in order to compare trends and look for outliers. *Context+focus* techniques may reduce the need for virtual navigation in some tasks, but are less useful when the relevant information is distant. Faced with this predicament, a user's natural response would be to reduce the amount of virtual navigation. This accommodating behavior may save precious time and reduce cognitive workload. Unfortunately, it may also contribute to a 'tunnel vision' phenomena, where analysis is focused on, and limited to a small fraction of the available data.

Large, High-Resolution displays

As display technology improves accompanied by a cost decline, larger displays with higher pixel density are becoming more prevalent. These displays make it possible to visualize more information, increase the visualization's level of detail, and simultaneously juxtapose multiple visual representations to show different aspects of the information space. Large, high-resolution displays tend to greatly reduce the amount for virtual navigation, which is replaced by embodied interactions such as eye movements and head turns [2], often accompanied by productivity gains [3, 4].

The effects of being able to see and interact with more information at once, however, may have important consequences in exploratory visual analysis scenarios. As information becomes instantaneously available on a large display, visual search sets in as the primary mechanism for information foraging. Attending to different pieces of information becomes be as easy as moving ones eyes across the screen, a far less costly alternative to virtual navigation [5]. The increased utilization of visual search also reduces the cognitive cost associated with frequent tasks such as visual comparison [6]. These changes in the cost structure of low-level visual analytic operations may ultimately have ramification on the user's higher-level analytic behavior. For instance, the user may invest more time comparing visual patterns in search for relationships. Alternatively, the user may choose to spend extra time exploring different hypotheses or narratives before drawing conclusions.

Previous research has shown that seemingly small changes in a visual analytic environment can significantly improve users' analytic strategy [7]. Can Large, High-resolution display

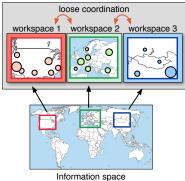


Figure 2. The coordinated workspaces model provides semiautonomous detailed views that can be juxtaposed on a large, high-resolution display. The workspaces are also loosely coordinated to respond collectively to brushing-andlinking operations. However, the contents of each workspace can be changed independently of the others. In this instance, three workspaces are used to visualize population centers in the US, Europe. and east Asia. we leverage the affordances of large, high-resolution displays to facilitate the exploration of large and complex information spaces? More specifically, can we promote diversity and broadness in exploratory visual analysis tasks by giving users access to larger displays with more pixels? Would this in turn impact the diversity of hypotheses articulated during the analysis?

Coordinated workspaces

To take advantage of the increase in display size and resolution, we employ a **coordinated workspaces** paradigm whereby the screen is divided into several workspaces that encapsulate semi-autonomous views. These workspaces essentially function as 'bins' or 'magnifying lenses' that can be juxtaposed on a large display and configured to show (or magnify) different parts of a large information space. For instance, when visualizing large population maps, one workspace can be set to magnify the North American region, a second could show Europe, while a third could show portions of Asia (see Figure 2). Workspaces can also be coordinated to collectively respond to brushing-andlinking operations similar to traditional coordinated multiple views [8]. Furthermore, workspaces can be independently re-configured to show different subsets of the data without disrupting the entire layout. By juxtaposing multiple workspaces side-by-side, the user can guickly consult divergent parts of the information space with eye movements and head turns. Moreover, with a high-resolution display, workspaces can visualize the relevant information at sufficient detail, eliminating the need for frequent virtual navigation.

This notion of a workspace is not new. In fact it is a standard feature in modern desktop systems [9]. Our model is also similar to Ware's *DragMag* [10]. However,

here we emphasize the fact that workspaces can be juxtaposed side-by-side on a large, high-resolution display so that they are all visible at the same time. This is important in exploratory analysis where context switching can be disruptive to the user's visual working memory, making low-level analytic operations such as visual comparison unnecessarily difficult and costly. The question is: what sort of high-level analytical benefits or overhead can we expect from the use of multiple coordinated workspaces on a large, high-resolution display?

Hypotheses

Our hypothesis is that the coordinated workspaces model would enable users to explore, compare, and contrast disparate parts of the information space with relative ease on a large, high-resolution display. We also hypothesize that this would eventually encourage users to observe more relationships, and thus formulate and explore more (competing) hypotheses and narratives, compared to conventional visualization interfaces.

User study

We conducted a pilot user study to investigate the above hypotheses. We had two general goals: first, we wanted to get a sense of how a user might utilize a visualization tool built around the coordinated workspaces model to explore a large dataset. Secondly, we wanted to understand how the user adapts his/her analytical strategy to take advantage of environment. Rather than attempting a full comparative experiment at this stage, we decided that we could learn more by closely observing one expert user who had a real-world dataset and a curiosity to explore it. Our user for this pilot study was a doctoral student in behavioral ecology and evolutionary biology, with research interests in the collective behavior of insects. The analysis of insect behavior is a particularly challenging problem that can benefit from new exploratory analysis tools. Insects exhibit stochastic, locally scoped movement patterns that are difficult to characterize on a case-by-case basis. To understand their behavior researchers record their movement in the field, collecting large samples of trajectories under varying conditions to tease out general responses. Due to the large number of plausible theories that could explain an observed movement pattern, researchers need a scalable way of exploring and testing different theories against their trajectory data.

Dataset, visualization, and apparatus

The dataset comprised approximately 500 Kenyan Seed Harvester ant trajectories that were captured under a variety of experimental conditions. The trajectories were obtained by tracking individual ants at approximately 3mm spatial resolution inside a designated experimental arena. We used a 19 Megapixels tiled display with a physical size of 23x10 feet (7x3 meters). The visualization environment divided the screen horizontally into a number of coordinated workspaces, which is specified by the user. Workspaces can be set to group collections of ant trajectories based on the experimental condition, thus allowing the researcher to juxtapose and compare different trajectory groups. Within each workspace, trajectories were arranged in a small-multiples layout. The workspaces were given distinct background tints to make them more distinguishable. Figure 3 illustrates the visualization environment. Additional details about the design decisions are described in [11].



Figure 3. The visualization environment employed in the pilot user study. Workspaces are given distinct background tint. Each workspace displayed a number of insect trajectories in a small-multiples layout (shown in the inset). Furthermore, workspaces can be configured to group trajectories based on specific experimental conditions. Brushing-and-linking actions propagate affect all trajectories across all workspaces.

Interactive features

Navigating the information space is achieved by modifying the type trajectories associated with workspaces using filters. For instance, one workspace can show trajectories of ants captured *east* of the colony's main foraging trail, while a second workspace might contain trajectories of ants captured *on the trail* while carrying a seed. To facilitate comparison and correlation, we included a visual cueing technique; a paintbrush tool lets the user brush the background of a single trajectory causing the visualization to highlight segments that intersect with the brush (see Figure 3, inset). Additionally, a temporal filter allows the user to limit rendering to trajectory segments that corresponds to motion within a specified time window (such as the first 10 seconds of the experiment).

| Type of interaction | Percent time spent interacting |
|-------------------------|-----------------------------------|
| Workspace management | 26% |
| Brushing and linking | 74% |

Table 1. Percentage breakdown of thetime spent interacting with thevisualization environment.

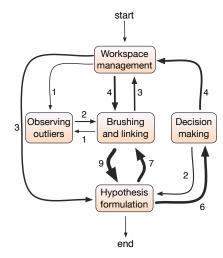


Figure 4. A state transition diagram illustrating key states in the user's analytic activity. The weights of the arrows indicate how many times a transition has occurred. That number is also indicated next to the arrow.

Methods

After a brief training, the participant was given an hour to explore and analyze her data and instructed to think aloud during the analysis. The session was video and audio-recorded, and a verbal transcript was produced. We used a two-pass coding scheme to analyze the data. The first pass focused on capturing the user's low-level interaction with the visualization environment (e.g. filtering, changing the layout, brushing-andlinking, etc...) as well as tagging any insights, questions, or hypotheses uttered by the user. The second pass focused on understanding the user's analytical strategy and how that strategy is shaped by the affordances of the visualization environment. At the end of the second pass, we created a state transition diagram that characterized the analytic activity at a high-level (see Figure 4).

Findings

As intended, the user utilized the coordinated workspaces to divide the large display into 'bins' that held distinct groups of trajectories for comparison. Often, the display was divided into 2-5 workspaces with each group displaying trajectories of ants captured under different experimental conditions. In total, the user was able to cover 416 out of 496 trajectories in the original dataset (approximately 84% of the data). These trajectories were visible at least once during the study, though we can't tell if the user looked closely at each one. We note, however, that a quick glance over trajectories is sufficient for most tasks when the linked paintbrush is used to highlight patterns of interest.

Once workspaces are configured, the user spent most of her time investigating relationships between the visible trajectory groups before moving on to different groups (see Table 1). Comparison was primarily done in place without disrupting the layout. Using the linked paintbrush tool and the temporal filter in concert, the user would specify a movement pattern she is curious about. The effects of brushing would propagate across all the workspaces, instantly highlighting trajectories that exhibited similar spatio-temporal patterns. The user would then investigate the highlight patterns, both within a workspace and across multiple workspaces. Interestingly, this activity coincided with the articulation of new hypotheses and questions in most of the time. Once a relationship is recognized and noted, the user would move on to test different patterns with no the need to change the layout or the contents of the workspaces. This behavior became evident from the frequent transitions between 'Brushing and linking' and 'Hypothesis formulation' in Figure 4. For instance, upon seeing that ants captured *east* of the colony's main foraging trail exhibit a direct movement towards the *west* side, the user brushed the *west* side and noticed a majority of them had a red highlight (see Figure 3, inset). This led the user to hypothesize that ants will attempt to head in the direction of the colony's trail when released in an effort to locate pheromone cues that will lead them back to the colony's nest. However, upon seeing how different workspaces react to brushing, the user would quickly articulate a different pattern to be tested, which would in turn trigger a new hypothesis. For example, upon seeing that ants captured on the trail did not exhibit a similar directed motion, the researcher proceeded to brush the center of a trajectory (corresponding to the point of release) with a green color, hypothesizing that "off-trail ants should start green and turn black faster [than their ontrail counterparts] because they know where they're going".

The ability to simultaneously see and interact with a large number of trajectories eliminated the need for frequent virtual navigation and reduced the cognitive cost associated with the analytical task. This appears to have encouraged the user to explore a wide range of relationships and follow up on multiple hypotheses. Although we didn't find evidence that the user was actively considering competing theories, our observations indicate that she was able to formulate and explore hypotheses that offered complimentary accounts. In total, the user was able to explore 11 distinct hypotheses within one hour.

Conclusions and future work

Our pilot study suggests a positive effect for using large, high-resolution displays in exploratory visual analysis scenarios. By dividing the screen estate into multiple coordinated workspaces, we can reduce the cognitive costs associated with conventional multi-scale interfaces. These low-level cognitive efficiencies could in turn encourage users to explore their data more broadly, and invest more time in formulating and testing complimentary hypotheses and narratives during the analysis. We are planning a larger comparative study to further investigate this phenomenon. To isolate the effects of the display size and resolution, we will vary those two variables between subjects. To make the scenario more suitable for subjects form the general population, the future study will utilize geospatial datasets.

Acknowledgements

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