EXPLORING COGNITIVE STRATEGIES FOR INTEGRATING MULTIPLE-VIEW VISUALIZATIONS

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Visualizing information is useful for finding patterns in complex data sets, but little research has been done on how people understand multiple-view visualizations (multiple visualizations presented simultaneously). A controlled experiment was performed using different combinations of visualizations and different task types as independent variables, and qualitative and quantitative data were collected. To collect the data psychological tests, logs of the participants' interaction, eye-tracking equipment, and video recordings were used. This paper reports a portion of the results from this experiment. Main findings include that, contrary to what was suggested in previous literature, the time cost for switching between different types of visualizations (context switching) may not be significant, and that displaying the data using the same type of visualization may cause interference. Orthogonal combinations appear to aid users in finding and recognizing patterns, and focusing attention and analogical reasoning on spatial relationships may be important cognitive abilities for the given tasks.

INTRODUCTION

Visualizing information can provide insight into complex data sets. Without visualization, using only statistics and tables of information, patterns would be harder to detect. Various companies and government agencies make use of information visualization for purposes ranging from credit card security to exploring the human genome to screening for terrorists. We hope that this study, in combination with follow-up research, will help in the creation of criteria to improve the design of these applications.

When visualizing information it can be presented in a single integrated view or in multiple coordinated views. The research literature presents two opposite lines of thought regarding multiple-view versus integrated-view visualization. On one hand, some authors emphasize the advantages of layering information and integrating more information in one view (Burns, 2000; Tufte, 1983). On the other side, different authors argue for the advantages of splitting information into multiple-views (Roberts, 1998).

If multiple-views are used, it is possible to present them simultaneously or sequentially. Burns studied what we refer to as both multiple-view and integrated-view visualizations presented synchronously and asynchronously (she categorizes these dimensions as low-space or high-space and low-time or high-time) (Burns, 2000). Related to what Burns would classify as low-time high-space, Trafton *et al.* studied multiple visualizations presented to Navy meteorologists sequentially (Trafton, Kirschenbaum, Tsu, Miyamoto, Ballas, & Raymond, 2000). In this paper we focus on multiple-view visualizations presented simultaneously (or high-time low-space). The multiple-view visualizations we used consisted of two visualizations connected in such a way that selecting data in one view would highlight related data in the other view. Figure 1 shows an example of a multiple-view system with coordinated views.

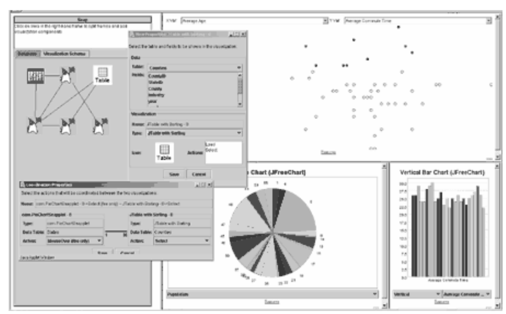

Figure 1. Screenshot of SNAP, a system showing multiple-view visualization (http://infovis.cs.vt.edu/snap/)

The intention of this research is to study the way in which people mentally integrate data from multiple-view visualizations by investigating how users identify the relationship between data in different views. The time cost of context switching is measured and the cognitive processes involved in multiple-view visualization are explored. The motivation for doing this research is at least three-fold. First, some guidelines (Baldonado, Woodruff, & Kuchinsky, 2000) for deciding when to use multiple-views are available, but surprisingly little has been done to confirm these. Second, there has been a growing interest in using multi-view visualization (North & Shneiderman, 2000; Suh, Woodruff, Rosenholtz, & Glass, 2002) and of understanding cognitive processes of users. Third, designing effective multiple view systems is a challenging task.

Guidelines for using multi-view systems suggest their use if the data contains diverse attributes, if correlations and/or disparities in data can be made apparent, or if a single view is overwhelming. A number of cognitive aspects are involved with their use including the time and effort to learn the system, the load on the user's working memory, the effort required for comparison, and context switching (Baldonado *et al.*, 2000). The cost of context switching between views is cited multiple times in these guidelines and is an important concern since a user must make use of numerous perceptual cues, and cognitive load may be increased. In this research, we are interested in measuring the cognitive aspects involved in multi-view systems.

Baldonado *et al.* (2000) also pointed out that besides occupying more space and requiring the learning of additional constraints, multiple view situations increase the demand on cognitive attention. This suggests that attention is a cognitive function that will drastically influence the user's performance. More specifically, the task will mostly involve the use of selective attention, where the user seeks information and searches for targets.

Wickens and Hollands (2000) stated that although selective attention can occur without a change in direction of gaze, most of the time it is still the case that, "our gaze is driven by our need to attend". Studying visual scanning behaviour, which is closely related to the concept of an attentional searchlight, can reveal insight into selective attention (Rock & Mack, 1994). For this reason, eye-tracking was used in this research.

It is important to note that the results presented in this paper are part of a larger work. The focus of another paper (Convertino, Chen, Yost, Ryu, & North, 2003) is the eye-tracking data and the logging of user interaction with the system. Here we present some of the basic findings from those aspects of the experiment, but also delve into the data obtained from the videotapes and from user comments.

METHOD

Design

The goal of this experiment was to gain insight into the cognitive strategies people use to mentally integrate multiple-view visualizations. We used a 4x4 factorial, within-subject design with 16 participants. The order of conditions for each subject was balanced by Latin-square design. Independent variables were the combination of visualizations and question types that varied in difficulty. The visualization system used in this study was implemented in OpenGL. This system supported the traditional interaction techniques (the ability to select a single point or to drag and select multiple points), and presented the user with pairs of visualizations displaying different attributes of the same data set. Using the brushing and linking interaction technique, if a point was selected in one view, the corresponding point was also highlighted in the other view. The given combinations were two parallel coordinate plots (PP), a parallel coordinate plot and a scatter plot (PS), a parallel coordinate plot and a geographic map (PG), and a scatter plot and map (SG) (Figure 2). All the subjects had been exposed to all four types of visualizations during their previous class work. The system was able to record the history of the users' actions and the corresponding completion time. The Iscan RK-464 eye-tracker was used to track subjects' eye movements.

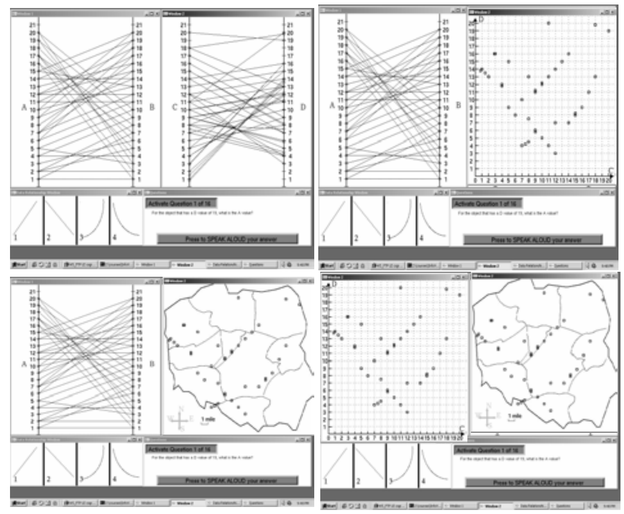

Figure 2. Combinations from top left clockwise: PP, PS, SG, PG. At the bottom left of each are the patterns, and the bottom right the question.

Table 1. Experimental design summary (within-subject)

	PP	PS	PG	SG
Question 1 (Single switch & Search)	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}
Question 2 (Multiple switch & Search)	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}
Question 3 (Single switch & Pattern)	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16} .
Question 4 (Multiple switch & Pattern)	s_1 ~ s_{16} .	s_1 ~ s_{16}	s_1 ~ s_{16}	s_1 ~ s_{16}

The data consisted of 40 data points with 4 attributes (A, B, C, and D). The data was abstract data in order to avoid the interference of previous experience. The A and B attributes were shown in the visualization in the left window and C and D in the right window. The subject was requested to identify relationships in the data. The relationships were always between 2 attributes, and involved 10 data points with 1 outlier. The PP condition represented the situation without any context switching, whereas the other three conditions required context switching because those involved pairs of different views (PS, SG, and PG). Within each of the four combinations, four different types of questions were given to differentiate task difficulty. Question 1 required searching for a given attribute, question 2 required searching for and finding the lower attribute when comparing two objects. Question 3 required finding a pattern between C and D values, and question 4 required finding a pattern between B and C values. Table 1 shows the design schema of the 4x4 factorial within-subject design.

Procedure

Sixteen subjects participated in two sessions. First, they provided demographics including their familiarity with different visualizations. They were given the Raven test for measuring the ability to form perceptual relations and to reason by analogy and three subtests of the Weschler Adult Intelligence Scale Revised (WAIS-R) including Digit Symbol, Picture Completion, and Digit Span Verbal subtests. Each of the subtests gives an index about some specific cognitive functions. The Digit Symbol performance subtest involves visual-motor coordination and speed. The Picture Completion performance subtest involves visual recognition, general information, and focusing attention. Finally, the Digit Span verbal subtest involves auditory attention, concentration, and short-term memory.

During the second session participants were given instructions, completed two practice tasks, and then performed 16 experimental tasks. During the practice tasks the subject could familiarize themselves with the system and the different visualizations. They were videotaped and asked to think aloud. After completing these tasks, they were asked to rate the difficulty on Likert scales of each question type and of using the four pairs of visualizations. Finally, they ranked their preference of combinations and questions.

RESULTS

User Performance

The completion time for each question was divided by the average completion time to account for individual pace. Figure 3 shows completion time per question type. Analysis of variance (ANOVA) was conducted and the result showed that PP took significantly longer than the others, F (3, 45)=11.32, p<0.001.

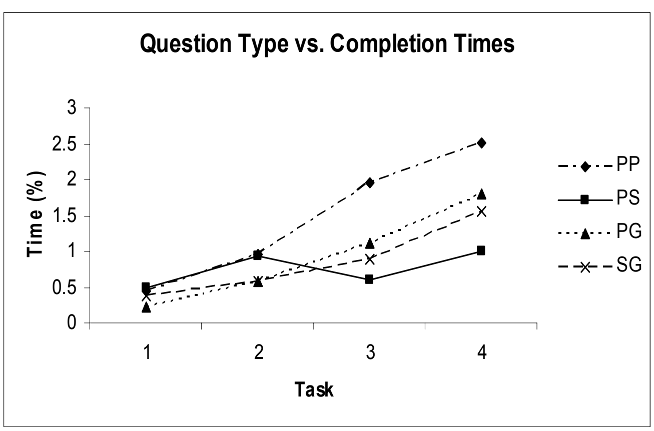

Figure 3. Completion times weighted by an individual's pace.

Subjects answered the most questions incorrectly with PP - 28 wrong answers out of 64 questions (16 subjects x 4 questions), and subjectively rated PP as the most difficult combination to use, but the difference was not significant using an ANOVA, $F(3, 45)=2.08$, p=0.117. PS was the best combination with the most correct answers as 14 wrong answers out of 64 questions (Table 2) and lowest completion times as shown in Figure 3. These results were opposite the hypothesis and literature since PP took longer than those presenting data in different manners. Familiarity with parallel coordinate plots was not correlated with completion time (r=-0.13). The difference in completion times may be a result of interference from the same visualization, or from lack of orthogonal representation.

Table 2. Wrong answers and average difficulty ratings

	Total number of wrong answers from 64 questions	Average difficulty rating (1=least difficult, 5=most difficult)
PP	28	3.25
PS	14	2.69
PG	24	2.50
SG	15	2.44

Subjective Rating

There was no significant difference between preference rank and difficulty rating based on the combination of visualizations. However, subjects did prefer and therefore rank the combinations according to their perceived level of difficulty (Table 2). This pattern did not hold for question types. The difficulty rating was the lowest for question type 1, and the highest for question type 4 as intended. They also preferred the questions involving a searching task. Additionally, subjects preferred the questions that required multiple visual switches between views to those that required a single visual switch.

Users were asked to comment on their opinions of the combinations of visualizations on the final questionnaire. Their responses confirmed that they found parallel coordinates the most difficult visualization to use. Five of the subjects commented that the map was the easiest type of visualization to use, while two commented that it was harder. Four of the subjects commented that relationships were harder to discover using parallel coordinates and that in general parallel coordinates were harder to use. Three subjects felt the opposite about parallel coordinates, preferring them to the other types of visualizations and ranking them the easiest to use. One usability issue when using parallel coordinates is that because the lines cross, it can be hard to select multiple edges. Another issue three subjects mentioned was the difficulty in keeping their heads still for the duration of the experiment (a necessity because of the eye-tracking equipment).

From the think-aloud data, it appears that when users were answering question type 4 and had to select a range of A values, and find a relationship between B and C values, much of the user's focus was directed toward selected the range of A values. Some users commented that finding patterns between attributes presented in different views was very challenging, and one said she did not know how to do it. Technical difficulties and time constraints have temporarily prevented more in-depth analysis of this data. However, the videos recordings also captured the screens and actions of users. Viewing these tapes will help discover how users took advantage of multiple-selection and when they chose to use single-selection over multiple-selection along with more details regarding their cognitive strategies. It should also provide insight into interaction strategies characterizing successful users.

Cognitive Abilities

From the WAIS-R given to each subject, the picture completion subtest scores showed relatively high correlation with completion time (r=-0.46) (Figure 4) and the number of errors (r=-0.4). The subjects' performance on the Raven test was correlated negatively with the number of errors on question 3 (r=-0.44) and the correlation increased in strength if question 1 and 3 were considered together (r=-0.52). The Raven test measures reasoning by analogy using a set of visual stimuli. During the test, each subject had to detect a relationship and then reapplied the same relationship to other stimuli by analogy.

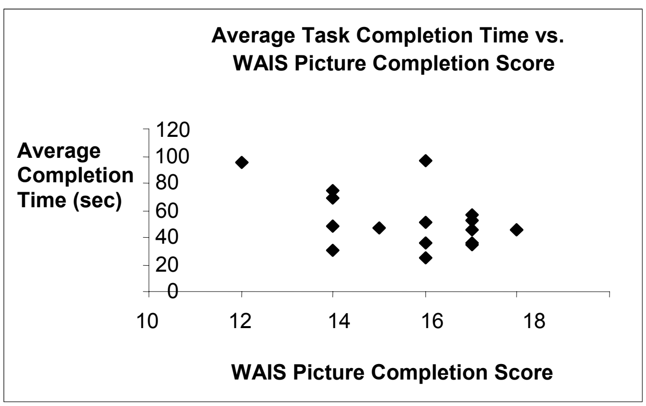

Figure 4. Higher Picture Completion scores correlated with lower completion time.

Eye-tracking Data

An eye-fixation is each instance that the eye remained in an area that was 5 pixels vertically and 3 horizontally for at least 40 milliseconds. The majority of fixation time within the right parallel coordinate plot was spent in between the axes. This suggests that users were looking at the slope of the lines and not at the values on the axes to determine patterns. It also appears that users that performed worse fixated on one location for longer periods of time. For more detailed eye-tracking results please refer to Convertino *et al.* (2003).

DISCUSSION

User Performance and Subject Rating

We had predicted that situations involving two parallel coordinate plots (PP) would take the least amount of time because there would be no cognitive load from context switching. The results were contrary to our hypothesis because questions involving the use of two parallel coordinate plots (PP) actually took significantly longer time to complete. This suggests that in some situations, cognitive integration may actually be more difficult when a person is presented with two identical visualizations. Another explanation is that users were able to match patterns easier when presented in a scatter plot since the choices were presented in an orthogonal manner. Results from the user comments on the final interviews and from the think-aloud data suggest finding patterns using parallel coordinates could be challenging, and that finding patterns across visualizations was hard. It should be noted that the strength of using parallel coordinates is that multiple attributes can be plotted in the same visualization and their use was intentionally simplified for experimental purposes.

Cognitive Abilities and Eye-Tracking Data

The relatively strong correlation between the picture completion subtest and task completion time suggests that the task required consistent involvement of visual recognition and focusing attention. In addition, the subjects' performance on the Raven test was correlated negatively with the number of errors on question types 1 and 3. Since the Raven test measures reasoning by analogy using a set of visual stimuli, this suggests that analogical reasoning is required to recognize relationships between two attributes in a single visualization, but is not as important when finding patterns across visualizations.

Results from the eye-tracker show that when the parallel coordinate plot was presented on the left the subjects spent most of their time looking at the axes. This was to be expected since most questions asked the subjects to use a subset of points from one of these axes. More interesting was the situation of PP. In this condition, subjects had to find patterns within the parallel coordinate plot on the right. Subjects actually spent most of their time looking at the area in between the two axes. This suggests that most of the subjects were looking at the slope of the lines, and not the values on the axes in order to find the pattern. For more details and discussion on the results of the eye-tracking, along with an additional discussion of 1-dimensional versus 2-dimensional selection when using different combinations of visualizations, please see (Convertino *et al.*, 2003).

Abstract Data Verse Domain Specific Data

Burns research has shown that high-time and high-space (or integrated view visualization) supports performance better than multiple-view visualizations presented either simultaneously or sequentially (Burns, 2000). She argues that the reason for this is that integrated-view visualizations are able to show the data in a meaningful way. That particular piece of research applied to a certain domain, specifically, to power plant operators. For that scenario, showing the data in a meaningful way could be based on domain knowledge.

In contraposition with that logic, the explicit purpose of our study was to avoid the influence of factors related to specific domains and focus on more general information visualization issues. The result of that decision is that our results do not apply specifically to any domain. However, they are important issues that should be considered during the process of designing a system for any domain, and particularly for situations where multiple-views are used for exploring unknown relationships in the data. Designers of multiple-view systems should consider the possible affects of using orthogonal views, and the possibility that interference may occur if similar visualizations are used.

CONCLUSION

We have explored the cognitive abilities involved in working with multiple-view visualizations and the effects of context switching. Using cognitive ability pretests we were able to find correlations between focusing attention, analogical reasoning, and performance. Additionally, our study has shown that context switching may not increase the difficulty of cognitive integration. Similar visualizations may cause interference resulting in decreased performance. An alternate explanation is that subjects had to mentally transform patterns in parallel coordinate plots to an orthogonal representation and this additional step reduced performance.

Future work includes evaluating different combinations of visualizations not explored in this research. Eventually, following efforts in this direction could result in developing a structured method for designing multiple-view visualization systems based on cognitive abilities, tasks, and datasets. For now, we recommend that designers of multiple-view systems consider using orthogonal combinations of visualizations, and that they are aware that cognitive interference may potentially occur if similar visualizations are presented simultaneously.

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