Exploring Context Switching and Cognition in Dual-View Coordinated Visualizations

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Abstract

Multiple-view visualizations are useful for finding patterns in complex data sets, but little research has been done on how they are used. We performed a controlled experiment to study the cognitive strategies and context switching by using combination of visualizations and different task types as independent variables and qualitative and quantitative data were collected. To collect the data, paper-based tests, logging of participants' interactions, eye-tracking, and think-aloud techniques and video recording were used. Unlike suggestions in literature, our results show that the time cost for context switching may not be significant and similar visualizations may actually cause more interference. Furthermore, orthogonal combinations appear to aid users in recognizing patterns. Focusing attention and analogical reasoning on spatial relationships may be important cognitive abilities as well.

Keywords: **Multi-View Visualization, cognition, context switching**

1. Introduction

We intend to study the way in which people integrate data from multiple views by investigating how users identify the relationship between data points in different views. The time cost of context switching is measured and the cognitive processes involved in multiple-view visualizations are explored. The motivation for doing this research is at least two-fold. First, although guidelines (e.g., [7]) for using multiple-view are available, no empirical study has been performed. Evaluation of guidelines would benefit future design process.

Second, there has been a growing interest in using multi-view visualization (e.g., [2]) and in understanding cognitive processes of multiple-view system [1, 3, 5]. These processes can provide insight into important aspects of designing the multiple-view systems, since finding these relationships among multiple views can be a difficult and challenging task.

Baldonado and coauthors [7] suggest the use of multiple-view visualization in three cases: if the data contains diverse attributes, if correlations and/or disparities in data can be made apparent, or if a single view is overwhelming. However, multiple view situations increase the demand on cognitive attention, since a user must make use of numerous perceptual cues, and thus cognitive load may be increased. Besides this, multiple-view visualizations occupy more space and require the learning of additional constraints.

Under such circumstances, context switching becomes an important concern. As a result, we are interested in measuring the cognitive aspects, especially context switching, involved in such systems.

Wickens and Hollands [3] 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 behavior, which is closely related to the concept of an attentional searchlight, can reveal insight into selective attention. For this reason, we tracked user's eyes movement in our experiment.

The tasks users performed in this study are search and finding patterns. These tasks mostly involved the use of selective attention. To collect data, paper-based tests, logs of interactions, eye-tracking, and think-aloud techniques with video recording were used. Trafton and coauthors [5] studied multiple-view visualizations which were sequentially presented to expert meteorologists.

2. Method

2.1 User Interface

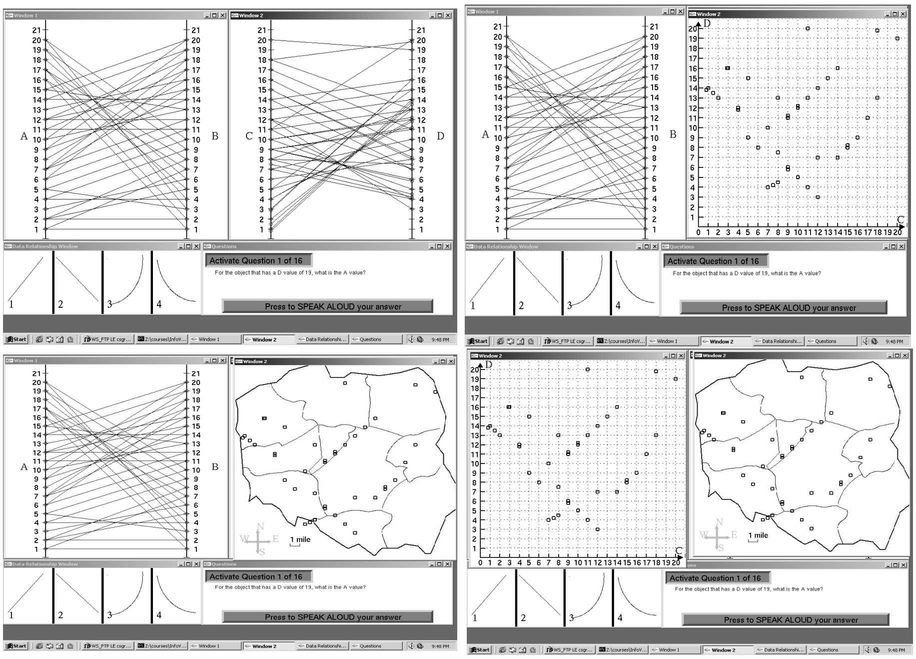

Figure 1. Combination for Experiments

From top left clockwise: PP, PS, SG, and PG. The bottom left of each is patterns and the bottom right is the questions.

The multiple-view visualization interface (Figure 1) is composed of four components: *two visualization scheme windows*, which is presented as the combination of two parallel coordinate plots (PP), or a parallel coordinate plot and a scatter plot (PS), or a parallel coordinate plot and a geographic map (PG), or a scatter plot and map (SG); one *answer window*, where uses can answer questions by mouse clicking; and a *question window*, where displays current questions we expect the subject to answer during experiment.

Such environment has several features, such as:

- *The use of generic coordination mechanisms*: A parallel coordinate plot, a scatter plot, and a geographic map were chosen because they have been widely used in many commercial software systems and were proved useful in the information visualization society. For instance, Tablelense for parallel coordinate display; Spotfire for scatter plot, and

In a parallel coordinate system, the axes of a multidimensional space are defined as parallel vertical lines separated by a certain distance. A point in Cartesian coordinates corresponds to a polyline in parallel coordinates.

- *Abstract data*: The data consist of 40 data points with 4 variates, displayed on four axes, A, B, C, and D. The data is purely abstract in order to avoid the interference of previous experience and the present context involved. The A and B attributes were displayed in the view on the left, as depicted in the figure above, and C and D in the view on the right.
- *Brushing-and-linking*: User can quickly construct common coordination. Our system, implemented in OpenGL, supports direct manipulation using the mouse as a pointing device. Brushing and linking [8] was implemented in a way that if a user select single/multiple edges in a view, the corresponding points/edges are also highlighted in the other view. This allows the user to build the relationship among data in different windows.
- *System log*: The system automatically loads the combinations of visualization and the questions during experiment study without the investigator's interference. Notice that a button is clickable so that user indicates the finish of the current question. Next question is loaded so that user can proceed. The system also records all user's interactions (e.g., mouse movements, clicks, data points chosen), task completion time, errors, etc.

2.2. Design

We used a 4x4 factorial, within-subject design with 16 participants (Table 1). The order of conditions for each subject was balanced by Latin-square design. Independent variables were the combination of visualizations and question types that vary with task difficulty. The tasks user performed in this study were search and pattern finding that require either single or multiple context switches. A total of 16 questions were asked during the study.

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 they 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 and 2 required searching, and question 3 and 4 required pattern recognition. Question 1 and 3 could be completed by selecting data in one view and seeing the results in the other view. Question 2 and 4 required a user to switch between views multiple times.

Visualizations / Question types	PP	PS	PG	SG
Single switch & Search	$S_1 \sim S_{16}$			
Multiple switch & Search				
Single switch & Pattern				
Multiple switch & Pattern				

Table 1. Design Schema

2.3. Procedure

Subjects participated in two sessions. During the first session, they filled out demographics forms including their familiarity with different visualizations. Then, the Raven cognitive ability test was performed to measure users' ability to form perceptual relations and to reason by analogy.

Three subtests of the Weschler Adult Intelligence Scale Revised (WAIS-R), including Digit Symbol, Picture Completion, and Digit Span Verbal subtests, were used. 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, subjects were first trained, i.e., they were told how to use the system (e.g., how to choose edges and points), and what are the two types of questions, followed by 2 practice tasks. This procedure lasts about 10-15 minutes.

After the practice tasks, the participants' eyes were tracked, using an ISCAN RK-464 eye movement monitoring system. A brief session was devoted to calibrating the eye tracking system along a five-point grid (the four corners of the screen and the center point). Following that the users had to answer 16 questions. The eye tracking was verified by having an experimenter sitting in the observation room to trace the users-eye. If the eye-tracking had drifted from the cross, the system was recalibrated. The recalibration time was not counted. Throughout the experiment, the subjects were videotaped and asked to think aloud.

After completing these 16 questions, they filled out a questionnaire for qualitative and quantitative measurements of the visualization strategies. They were asked to rate the difficulty of each question and of the four pairs of visualizations using Likert scales. They also ranked their preference of combinations and questions.

2.4. Participants

Participants are sixteen undergraduate computer science department students from an HCI class, 14 males and 2 females between the ages of 18 and 25. They received extra credits for attending this experiment. All subjects have been exposed to all the three types of visualizations during their previous class work.

3. Results

3.1. User Pe rformance and Subjective Response

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

Table 2. Number of wrong answers and average difficulty ratings

Figure 2 shows completion time per question type. The completion time for each question was divided by the subject's average completion time to account for pace. Analysis of variance (ANOVA) was conducted and the result showed that PP took significantly longer than the others, $F(3, 45)=11.32$, $p<0.001$.

Subjects incorrectly answered most questions with PP as 28 wrong answers out of 64 (16 subjects x 4 questions, see Table 2) questions and subjectively rated PP as the most difficult combination to use, but the difference was not significant with ANOVA, $F(3, 45)=2.08$, $p=0.117$.

PS was the best combination with most correct answers as 14 wrong answers out of 64 questions (Table 2) and lowest completion times (Figure 2). These results were opposite to the hypothesis in the literature, since PP took longer than those presenting data in different visualization strategies. 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.

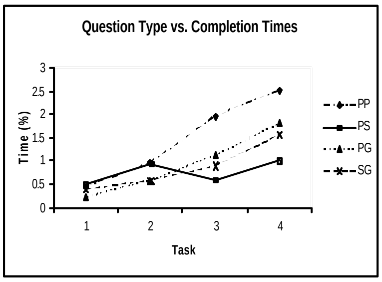

Figure 2. Completion times weighted by an individual's pace.

3.2. 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) (Table 2) and the number of errors (r=-0.4). The subjects' performance on the Raven test correlated negatively with the number of errors on question 3 (r=-0.44) and the correlation increased in strength if questions 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 reapply the same relationship to other stimuli by analogy.

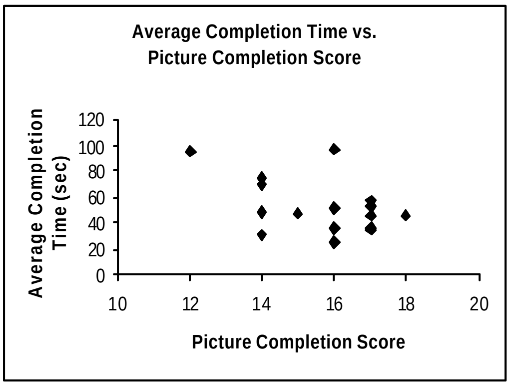

Figure 3. Higher Picture Completion Scores Correlated with Lower Completion Time.

3.3. 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. Figure 4 shows the percent of total fixation time that was spent fixated on each aspect of the parallel coordinate plot. Note that more time was spent looking in between the axes for the parallel coordinate plot on the right.

From the qualitative analysis of eye-movement trace [4] of the users we considered the differences within the 2 extremes in the distribution of performance. We looked at the two subjects that missed the largest number of question and the two that missed the smallest number of questions. The subjects with worse performance

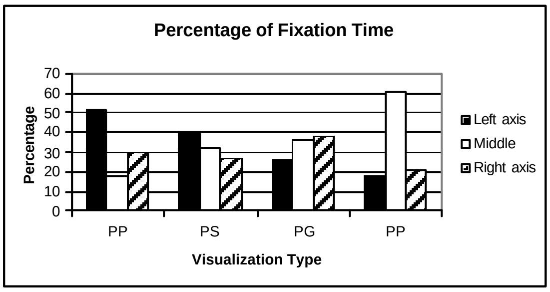

Figure 4. The percentage of fixation time for parallel coordinate plots (Note: the axes referred to in the left PP are from the left parallel coordinate plot. The axes referred to in the right PP are from the right parallel coordinate plot.

tended to have lower values of total fixations, total area path length, and average scan path length. Moreover, analyzing the fixations suggests that subjects with shorter fixation times may have performed better in general. An example of these patterns can be seen in Figure 5.

From the eye-tracking data (raindrop fixation scan path display charts) we observed that the subjects with the most wrong answers tended to look longer at specific locations (see Figure 6) and had a larger number of

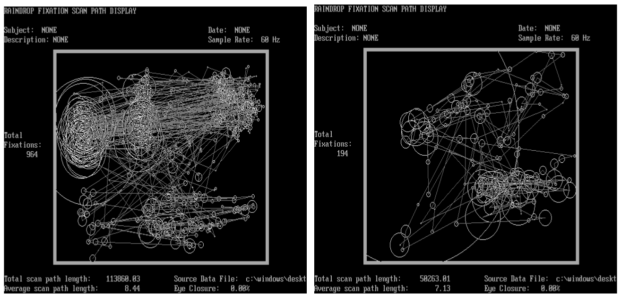

Figure 5. The left is the eye-movement trace for PG4 of a subject that answered the question correctly. On the right is the eye-movement trace for a subject that answered the same question incorrectly.

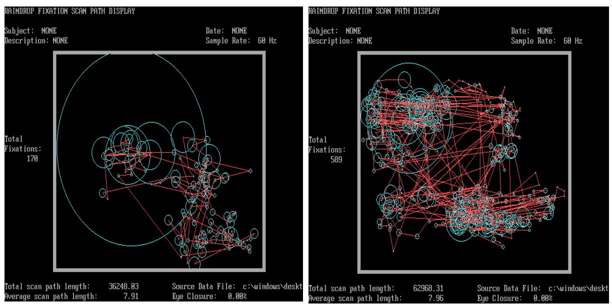

Figure 6. Both are the eye-movement trace for SG3 of 2 subjects. Left gave the wrong answer, whilst the right gave the correct one.

clicks within the same task.

4. Discussion

Four cognitive aspects involved with an information management task include: the time and effort to learn the system, the load on the user's working memory, the effort required for comparison, and context switching [6]. Context switching is not the dominant factor, but it does play a significant role.

Scatter plots allow "comparative visualization" providing an excellent visualization display method most appropriate in some case to understand the data. It is very familiar to researchers, and can be used for cross checking verification of data.

4.1. User Performance

We predicted that situations involving 2 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 and questions involving the use of 2 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.

4.2. Subjective Rating

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

4.3. Cognitive Abilities

The relatively strong correlation between the picture completion subtest and completion time suggests that this visualization strategy requires consistent involvement of visual recognition and focusing attention. In addition, the subjects' performance on the Raven test is correlated negatively with the number of errors on question 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.

4.4. Logging Data

In our logging data, there were three types of mouse action recorded: the number of clicks on edges or points, the number of clicks on empty space, and the number of clicks resulted in multiple selections.

With the dependent measure as the number of clicking edges, both visualization type and question type are significant with ANOVA, $F(3, 45)=3.49$, $p=0.023$ and $F(3, 45)=7.28$, $p<0.001$ respectively. For the number of clicking nothing, both visualization type and question type are significant with ANOVA, $F(3, 45)=3.01$, $p=0.040$ and $F(3, 45)=11.00$, $p<0.001$ respectively. However, multiple selection as a dependent measure, question type was the only significant factor, $F(3, 45)=8.03$, $p<0.001$. There is a correlation of total number of clicks and raw completion time (0.66). There is no correlation between the number of time of subject and their completion time (0.14).

4.5. Eye-Tracking Data

Results from the eye-tracker show that when the parallel coordinate plot is presented on the left the subjects spent most of their time looking at the axes. This is to be expected since most questions require the subjects to use a subset of points from one of these axes. More interesting is the situation of PP combination in which the subjects have to find patterns within the parallel coordinate plot. 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.

5. 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 are able to find correlations between focusing attention, analogical reasoning, and performance. Additionally, our study shows 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 have to mentally transform patterns in parallel coordinate plots to an orthogonal representation and this additional step reduces performance.

Future work includes evaluating different combinations of visualizations not explored in this research, for example, the combination of two scatter plots and two map views. Also we plan to deepen our analysis of the eye-tracking data and think aloud data recorded. Eventually, following efforts in this direction could result in developing a structured method for designing multiple-view visualization systems based on cognitive abilities.

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