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 cognitive strategies and context switching by using combination of visualizations and different task types as independent variables, and collecting qualitative and quantitative data. To collect the data paper-based tests, logging of participants' interactions, eye-tracking, think-aloud techniques, and video recordings were used. Unlike suggestions in literature, our results show that when considering dual-view visualizations 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 are important cognitive abilities as well.

1. Introduction

We studied the ways 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 was measured and the cognitive processes involved in multiple-view visualizations were explored. The motivation for doing this research was at least two-fold. First, although guidelines for using multiple-view visualizations are available [2], to our knowledge no empirical studies have been performed. The studies most closely resembling ours have been done on presenting different single visualizations sequentially [15], not on multiple visualizations presented simultaneously. Evaluation of guidelines for multiple-view visualizations (multiple visualizations presented simultaneously) would benefit the future design process.

Second, there has been a growing interest in using multi-view visualizations [5, 10, 12] and in understanding cognitive processes involved with the use of multiple-views [11, 13, 16]. Understanding cognitive processes can provide insight into important aspects of designing multiple-view systems since finding relationships in data distributed across multiple views can be a difficult and challenging task.

Current guidelines suggest the use of multiple-view visualizations 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 of the data would be overwhelming [2]. However, the use of multiple-view visualizations increases the demand on cognitive attention since a user must make use of numerous perceptual cues simultaneously, thus increasing cognitive load. Aside from increasing cognitive load, 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 the time it takes for context switching, involved in such systems.

Wickens and Hollands [16] state that although selective attention can occur without a change in direction of gaze, most of the time it holds true that, "our gaze is driven by our need to attend". Therefore, studying visual scanning behavior (which is closely

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related to the concept of an attentional searchlight) can reveal insight into selective attention. It is for this reason that we tracked eyes movements in this experiment. Users in this studied performed one of two types of tasks: search tasks, or pattern recognition tasks. Both of these task types involve the use of selective attention.

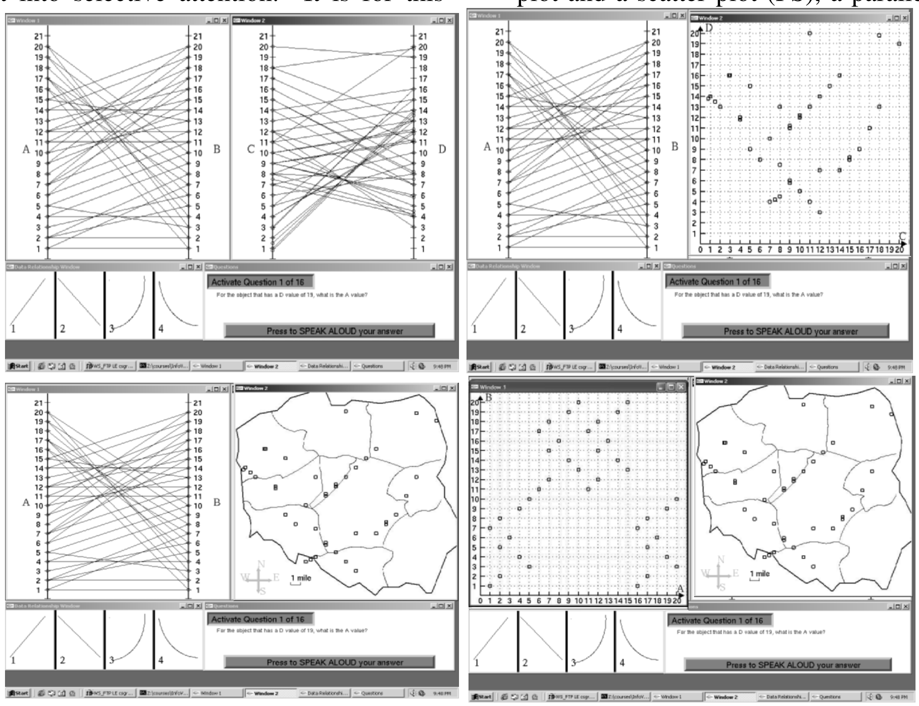

Figure 1. Combinations of visualizations used in the experiment.

From top left clockwise: two parallel coordinate plots (PP), a parallel coordinate plot on the left and a scatter plot on the right (PS), a scatter plot on the left and a geographic map on the right (SG), and a parallel coordinate plot on the left and a geographic map on the right (PG). Displayed at the bottom left of each combination are the choice of patterns and at the bottom right is the question.

In addition to recording the eye movements of participants in this study, data was also collected using various other means. These means included paper-based cognitive tests, system logs of user interaction in terms of clicks that selected edges, clicks that initiated multiple selection, and edges that were highlighted, the think-aloud technique, and video recordings.

2. Method

2.1. User interface

The dual-view visualization interface used in this study (Figure 1) was designed from scratch. It consisted of four components: *two visualization scheme windows*, presented as the combination of two parallel coordinate plots (PP), a parallel coordinate plot and a scatter plot (PS), a parallel coordinate plot and a geographic map (PG), or a scatter plot and geographic map (SG); one *question window*, where users were able to activate a question by clicking on one button, and indicate that they were finished answering the question by mouse clicking on a different button; and a *pattern window* that showed users four possible relationships that could be found when performing a pattern recognition task.

The dual-view visualization interface includes the following features:

- *The use of generic visualizations*: A parallel coordinate plot, a scatter plot, and a geographic map were chosen because they have been used in commercial software systems, and have proven useful in the field of information visualization. The advantages of using parallel coordinate plots are outlined in [9], and some commercial tools such as Spotfire [1] use an interactive scatter plot as the basic visualization.

  In a parallel coordinate plot, the axes of a multidimensional space are defined as parallel

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vertical lines separated by a specified distance. A point in Cartesian coordinates corresponds to a line in parallel coordinates. This visualization was kept consistent throughout three of the combinations in order to reduce influence due to previous experience.

- *Abstract data*: The data used in this study consisted of 40 data points. These 40 data points represented 10 different abstract objects each having a single A, B, C, and D attribute. The data was intentionally kept purely abstract in order to avoid any interference due to expectations of patterns due to experience with similar real world data. The A and B attributes were always displayed using the visualization on the left, and the C and D attributes were always displayed using the visualization on the right.
- *Brushing-and-linking*: Our system is implemented in OpenGL and supports direct manipulation using the mouse as a pointing device. Coordination between the visualizations was provided using brushing and linking [3]. Brushing and linking was implemented in such a way that if a user selected either single or multiple edges in one of the visualizations, the corresponding points and edges (representing the object's other attributes) were highlighted in the other visualization.
- *System log*: The system automatically loaded the combinations of visualizations and the questions during the experiment without the investigators' interference. Notice that a button was clickable that allowed users to indicate that they had found the answer to the current question. After clicking on that finish button, the next question was loaded and the user proceeded. The system also recorded all user interactions (mouse movements, clicks, data points chosen), and calculated the task completion time.

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 the question type (this varied based on task difficulty). The tasks user performed in this study were search tasks and pattern recognition tasks that required either single or multiple switches between views.

A total of 16 questions were asked during the study. The relationships participants were asked to find were always between two attributes, and involved ten abstract objects. To prevent participants from simply viewing three of the object's attributes and coming to conclusions, one of the objects always included relevant attribute values that were outliers. The PP condition represented the situation without any context switching, whereas the other three conditions required context switching because they involved combinations of different types of visualizations (PS, SG, and PG).

Table 1. Design schema

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

Within each of the four combinations of visualizations, four different types of questions were given. These four questions were of increasing difficulty. Question types 1 and 2 required searching, and question types 3 and 4 were considered more difficult because they required pattern recognition. Question types 1 and 3 could be completed by selecting data in one view and seeing the results in the other view. Question types 2 and 4 required a user to switch between views multiple times. An example of question type 1 is asking what the corresponding A value is for an object with a specified C value. An example of question type 2 is asking what the lower A value is when comparing objects with two different specified C values. An example of question type 3 is asking what the relationship was between C and D values for all objects with B values in a given range. Finally, an example of question type 4 would be to ask what the relationship between B and C values was for all objects with A values within a specified range. Note that this is considered a multiple switch task because the B and C attributes were located in different visualizations.

2.3. Procedure

Subjects participated in two sessions. During the first session they filled out demographics forms and

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included ratings of their familiarity with different visualizations. Then, the Raven cognitive ability test was performed to measure ability to form perceptual relations and to reason by analogy [4].

Three subtests of the Weschler Adult Intelligence Scale Revised (WAIS-R), including the Digit Symbol, the Picture Completion, and the Digit Span Verbal subtests were used [14]. 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 trained regarding how to use the system. They were shown how brushing and linking worked and how to select single or multiple edges and points. The concept of the abstract objects with four data attributes was also explained. As part of this training period, they were given two simple practice tasks. This procedure lasted approximately 10-15 minutes.

After the practice session concluded, the ISCAN RK-464 eye movement monitoring system was calibrated. This system is used to track eye movements and was recording the eye position at a rate of 60Hz. Following the calibration, participants proceeded through the experiment, eventually answering a total of 16 questions. To verify that the eye was being tracked appropriately one of the experimenters sat in the observation room watching the output. If the system lost calibration, the system was recalibrated before the start of the next question. Throughout the experiment the participants were videotaped and asked to think aloud.

After completing the 16 questions, participants filled out a questionnaire that included both qualitative and quantitative questions. Responses to these questions were used to identify cognitive strategies for answering different types of questions and used with different combinations of visualizations. The questions asked participants to rate the difficulty of each question and of using each of the four pairs of visualizations. Another question asked participants to rank their preference of combinations of visualizations.

2.4. Participants

Participants consisted of sixteen undergraduate computer science students from a human-computer interaction class. Fourteen males and two females between the ages of 18 and 25 participated. All participants received extra credit for their time. This particular demographic group was chosen because all of the subjects had been exposed to all three types of visualizations during their previous class work. This class work included exposure to parallel coordinate plots, a characteristic not typically found in the general population.

3. Results

	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)	3.2	2.6	2.5	2.4

3.1. User performance and subjective response

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. An analysis of variance (ANOVA) was conducted and the results showed that PP took significantly longer than the other combinations, $F(3, 45)=11.32$, $p<0.001$.

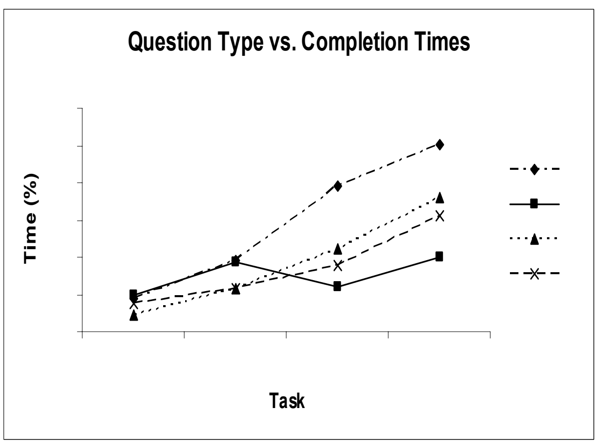

Figure 2. Completion times weighted by an individual's pace.

Subjects incorrectly answered the most questions using PP. For PP, 28 answers were wrong out of a possible 64 (16 subjects x 4 questions, see Table 2) questions, and participants 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. There were 14 wrong answers out of 64 questions (Table 2), and PS had the lowest completion times (Figure 2). These results were opposite the hypothesis in the literature regarding the increased time for context switching between different visualizations since PP took longer than the other combinations. Familiarity with parallel coordinate plots was not correlated with completion time (r=-0.13). Possible reasons for the difference in completion times include interference from using the same visualization, or lack of orthogonal representation.

Table 2. Number of wrong answers and average difficulty ratings.

3.2. Cognitive abilities

From the WAIS-R test given to each subject, the picture completion subtest scores showed relatively high correlation with completion time (r=-0.46) (Figure 3) and the number of errors (r=-0.4). The subjects' performance on the Raven test correlated negatively with the number of errors on questions of type 3 (r=-0.44) and the correlation increased in strength if question types 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.

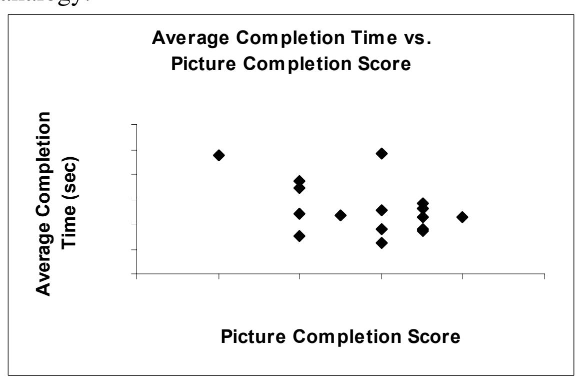

Figure 3. Higher picture completion scores correlated with lower completion times.

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.

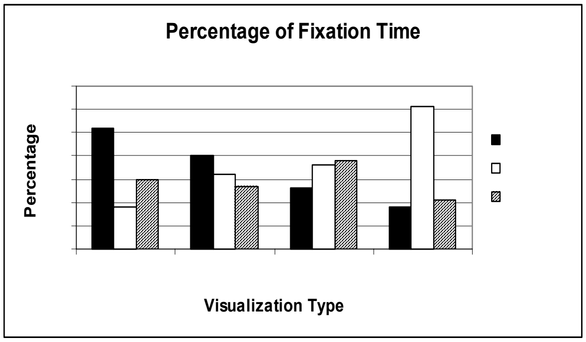

Figure 4. The percent of fixation time for parallel coordinate plots.

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.

From the qualitative analysis of eye-movement traces [17] of the users we considered the differences between the two subjects that missed the largest number of questions and the two that missed the smallest number of questions. The subjects with the worst performance tended to have lower numbers of fixations, less total area covered by their eye movements, and lower average scan path lengths. 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 clicks within the same task. Note that the size of the circles in Figures 5 and 6 represent the amount of time a user spent fixated on the location at the circle's center.

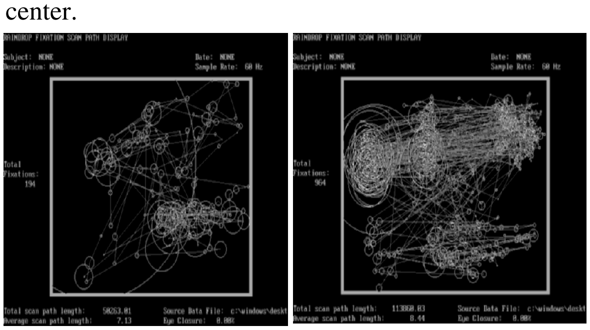

Figure 5. Eye-movements of a subject that answered PG4 incorrectly, and one that answered correctly.

On the left is the eye-movement trace for PG4 of a subject that answered the question incorrectly. On

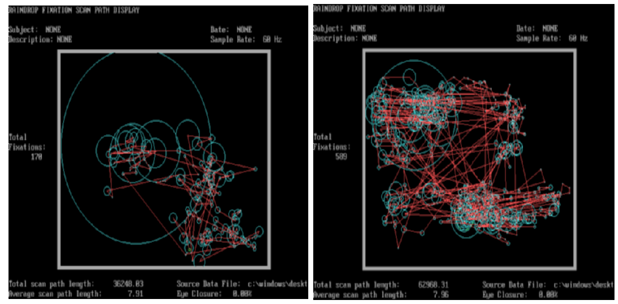

Figure 6. Eye-movements of a subject that answered SG3 incorrectly, and one that answered correctly.

The left is the eye-movement trace for SG3 of a subject that answered the question incorrectly. On the right is the eye-movement trace for a subject that answered the same question correctly.

From the results of the eye-tracking data we were also able to calculate the number of times participants visually switched between the two visualizations. This appears to be consistent with the trend for completion times in the sense that both time and the total number of switches between views increased based on task difficulty, and combination of visualizations (Figure 7). This was also consistent with the selection of edges in the sense that as the task difficulty increased so did the number of edges participants selected. Considering the global quantitative comparison using a t-test, we observed that the difference in the number of switches was not related to the correctness of participants' answers. The two main factors influencing the number of switches were the type of task and the combination of visualizations.

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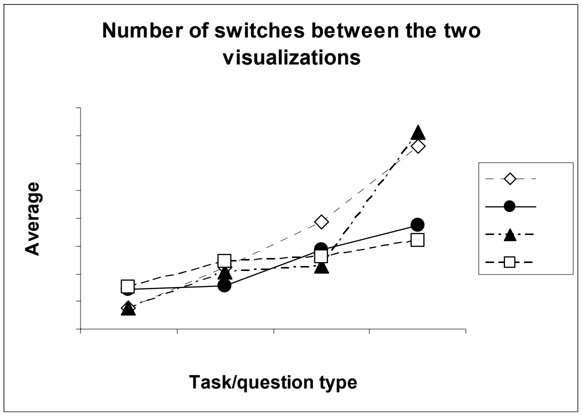

Figure 7. Number of visual switches between visualizations based on eye movement.

3.4. Logging data

In our logging data, there were three types of mouse actions recorded: the number of clicks on edges or points, the number of clicks on empty space, and the number of clicks initiating multiple selections. Using the number of edges selected as a dependent measure, both visualization type and question type are significant using an ANOVA for analysis, $F(3, 45)=3.49$, $p=0.023$ and $F(3, 45)=7.28$, $p<0.001$, respectively. For the number of times a user clicked empty space (meaning they either wished to clear their selected edges or they accidentally missed selecting an edge), both visualization type and question type are significant ($F(3, 45)=3.01$, $p=0.040$ and $F(3, 45)=11.00$, $p<0.001$ respectively). However, when considering the number of times multiple selection was used, question type was the only significant factor, $F(3, 45)=8.03$, $p<0.001$. There also exists a correlation between the total number of clicks and the raw completion time ($r = 0.66$).

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 [2]. 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. They are very familiar to researchers, and can be used for cross checking or verification of data.

4.1. User performance

We 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: questions involving the use of two parallel coordinate plots (PP) actually took significantly longer to complete. This suggests that in some situations, cognitive integration may actually be more difficult when a person is presented with two identical visualizations. However, further research is needed to determine if this is simply a phenomenon that exists when using two parallel coordinate plots.

4.2. 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 ranked the combinations according to their perceived level of difficulty. The difficulty rating was the lowest for question type 1, and the highest for question type 4 as intended. Although subjects preferred the questions involving search tasks (1 and 2) to the pattern recognition tasks, they also preferred the questions that required multiple switches between views (2 and 4) to those which required a single visual switch (1 and 3) despite their increased level of difficulty.

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 types 1 and 3 (single switch search and single switch pattern recognition tasks). 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. Eye-tracking data

Results from the eye-tracking data 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 combinations in which the subjects have 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.

The purpose of using the eye tracking data was twofold. On one side, we were able to validate initial hypotheses by integrating eye tracking data with logging data following the approach that other authors have used [8]. The other purpose was to use this tool in a heuristic way to discover typical strategies used for accomplishing the given tasks.

4.5. Selection between combinations

Different combinations of visualizations allow for different types of interaction. One area that differentiates combinations is the type of selection that is afforded. If the view from which the user wishes to select a subset of data is presented in an orthogonal manner, such as a scatter plot, this allows 2D selection. In other words, a user can drag along the x-axis to select a specified range of x values, and then drag upward in order to select a subset of y values for those x values. This type of interaction allows users to easily perform tasks such as those presented in question type 4. In question type 4 tasks users were given a specified range of values along the x-axis and were asked to find the relationship between y values and an attribute displayed within the other visualization. Hence, by maintaining the correct x interval the user could drag the multiple selection box up and down to view the result of increasing the y value for a given x range on an attribute in the other visualization.

While the use of a scatter plot allows for 2D selection, trying to find patterns when selecting two specified ranges of values from parallel coordinate plots can be a difficult task because of the 1D selection it affords. If a user wished to answer a task associated with question type 4, they could attempt to select the specified range on the first axis and drag the multiple selection box up and down. The problem with this strategy is that, because the x and y dimensions are not orthogonal, as they drag it up and down the corresponding points on the second axis typically will not increase and decrease in a standard manner. This type of 2D versus 1D selection provides any combination of visualizations that include a scatter plot or other orthogonal combination a definite advantage. Orthogonal axes provide the possibility of working on an intersection of a range of data on one axis and a range of data on another axis. An additional issue with using parallel coordinates, based on observation of participants' performance, was the rectangular selection box made it difficult not to select more edges than desired, especially with increased numbers of edge crossings.

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5. Conclusion

We have explored the cognitive abilities involved in working with dual-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 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.

6. Future work

Future work directly related to this study includes evaluating different combinations of visualizations not explored in this research. One important extension of this work is to evaluate the combination of two scatter plots and two geographic views to determine if these results were specific to parallel coordinate plots. Before moving on to that phase, we plan to deepen our analysis of the eye-tracking data and analyze the think aloud data that was collected. Another possibility is to carry out a cognitive dimensions analysis to identify correlations between some of the dimensions of the visualizations as outlined in [6] and the result of our analysis.

Following efforts in this direction could result in developing a structured method for designing multiple-view visualizations based on cognitive abilities. Additionally, our grand vision is to extend this work into a comparison of multiple-view visualizations and integrated-view visualizations (like those produced using ViA [7]) to determine when each is appropriate and advantageous.

7. References

[1] C. Ahlberg and E. Wistrand, "IVEE: an Information Visualization and Exploration Environment", In Proceedings of *InfoVis 1995*, IEEE, pp. 66-73, 142-143.

[2] M.Q. Baldonado, A. Woodruff, and A. Kuchinsky, "Guidelines for Using Multiple Views in Information Visualization", In Proceedings of *AVI2000*, Palermo, Italy, pp. 110-119.

[3] R.A. Becker and W.S. Cleveland, *Brushing Scatterplots*, in *Dynamic Graphics for Statistics*, W.S. Cleveland, Editor. 1988, McGill.

[4] P.A. Carpenter, M.A. Just, and P. Shell, "What One Intelligence Tests Measures: A Theoretical Account of the Processing in the Raven Progressive Matrices Test", *Psychological Review*, Publisher, City, 1990, pp. 404-431.

[5] R.M. Edsall, A.M. MacEachren, and L. Pickle, "Case Study: Design and Assessment of an Enhanced Geographic Information System for Exploration of Multivariate Health Statistics", In Proceedings of *IEEE Symposium on Information Visualization*, IEEE, pp.

[6] T.R.G. Green and M. Petre, "Usability Analysis of Visual Programming Environments: A 'Cognitive Dimensions' Framework", *Journal of Visual Languages and Computing*, Publisher, City, 1996, pp. 131-174.

[7] C.G. Healey, R. St. Amant, and M. Elhaddad, "ViA: A Perceptual Visualization Assistant", In Proceedings of *28th Applied Imagery Pattern Recognition Workshop*, Washington, D. C., pp. 1-11.

[8] A.J. Hornof and T. Halverson, "Cognitive Strategies and Eye Movements for Searching Hierarchical Computer Displays", In Proceedings of *CHI 2003*, ACM, Ft. Lauderdale, FL, USA, pp. 249-264.

[9] A. Inselberg, "Multidimensional Detective", In Proceedings of *InfoVis '97*, IEEE, Phoenix, AZ, USA, October 1997, pp. 100-107.

[10] C. North and B. Shneiderman, "Snap-Together Visualization: A User Interface for Coordinating Visualizations via Relational Schemata", In Proceedings of *AVI2000*, pp. 128-135.

[11] I. Rock and A. Mack, *Attention and Perceptual Organization*, in *Cognitive Approaches to Human Perception*, S. Ballesteros, Editor. 1994, Lawrence Erlbaum Associates Inc.

[12] J. Seo and B. Shneiderman, "Interactively Exploring Hierarchical Clustering Results", *IEEE-Computer*, Publisher, City, 2002, pp. 80-86.

[13] B. Suh, et al., "Popout Prism: Adding Perceptual Principles to Overview+Detail Document Interfaces", In Proceedings of *CHI '2002*, pp. 251-258.

[14] G.E. Taub, "A Confirmatory Analysis of the Wechsler Adult Intelligence Scale-Third Edition: Is The Verbal/Performance Discrepancy Justified?" *Practical Assessment, Research & Evaluation*, Publisher, City, 2001, pp. Electronic jounal; article has 9 pages.

[15] J.G. Trafton, et al., "Turning Pictures Into Numbers: Extracting and Generating Information from Complex Visualizations", *International Journal of Human-Computer Studies*, Publisher, City, 2000, pp. 827-850.

[16] C.D. Wickens and J. Hollands, *Engineering Psychology and Human Performance*, Prentice Hall, Place Published, 1999.

[17] D.S. Wooding, "Fixation Maps: Quantifying Eye-Movement Traces", In Proceedings of *ETRA'2002*, pp. 31-36.

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