Effects of Large, High-Resolution Displays for Geospatial Information Visualization

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(ABSTRACT)

Geospatial visualizations are becoming a larger part of society. From using maps to go from one location to another to using battlefield visualizations to help the military, geospatial visualizations are becoming a larger part of people's lives.

At the same time, large displays are becoming more prominent in people's lives. From large fifty-monitor tiled displays to dual monitor desktop systems people are using larger displays more often in their daily lives.

This dissertation summarizes our work with large displays and geospatial visualizations. We show dramatic increases in performance of more than ten times performance improvement when using larger displays that offer a greater number of pixels. We show performance improvements for a range of tasks from simple navigation to complex pattern finding tasks.

This dissertation contributes to the fields of human-computer interaction and information visualization in that it shows performance improvements as analytical force multipliers and explains why such performance exists. It explains how virtual navigation (mouse and keyboard input) correlates to physical navigation (body movement) to explain performance improvements. In addition, this dissertation explains how semantic zooming, space scale, task scale, and task type all are variables that influence human behavior in both navigation and performance.

This dissertation addresses primarily geospatial information visualizations, but extends to other generic spatially oriented visualizations. The impacts of large displays for both geospatial information visualizations and generic spatially oriented visualizations are explained.

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Table of Contents

List of Figures

List of Tables

Chapter 1 Introduction

The field of information visualization is concerned with garnering insight from data. The late Richard Hamming, a founder of the ACM, stated, "The purpose of computing is insight, not numbers" [56]. Information visualization helps to fill that purpose by showing, or visualizing, data for that express purpose.

In order for the field of information visualization to fulfill its goal of providing insight people must perceive their data in a meaningful way. Wickens explains that perception is "[r]aw sensory data relayed to the brain … given meaning" [159]. Visual perception then is to give meaning and understanding to visual sensory data.

Pirolli indicates that the greater the amount one can see at once, the greater the possible perception and resulting possible understanding [104]. The implications of his theory are that larger viewports can show more data than smaller viewports and thus the larger the viewport the more data shown and the greater the potential of insight into the data.

However, almost all visualizations are designed for and used on only a single monitor. As a result, a large potential is not used.

Large amounts of effort have been put forth to maximize the usage of small displays. For example, Keim, et al. created Pixel Bar Charts, a visualization technique that utilizes nearly every pixel on the display allowing for a million pieces of information to be seen at once on a standard monitor [74].

Abstract visualizations such a Pixel Bar Charts are able to take advantage of nearly all of the display space due to the nature of the abstract data not having a spatial dimension. However, spatially-centric data, especially geo-spatial data, require a spatial context which requires more overview information which translates into larger screen space requirements per data object.

This spatial context can be exacerbated by other factors as well such as a time dimension. For example, Kapler, et al. created GeoTime, a geospatial visualization tool that takes geospatial events and their corresponding time sequences into account [73]. Where Pixel Bar Charts can use nearly every pixel on the display, geospatial visualizations, such as

GeoTime, are largely restrained by more limiting factors such as spatial distances and time. In addition, GeoTime has additional constraints of connecting lines between events which add occlusion as another factor. In general, any geospatial visualization has some sort of map, or map-like base associated with it.

Maps have existed for thousands of years. According to historians, the oldest known maps were written on clay tablets from the Babylonian era from about 2300 B.C. [21]. Maps were later created extensively on other forms of material such as papyrus then later paper. Paper has been the main material used for printing or writing maps for the last several hundred years. Recently, there has been a surge in the use of map making and map usage with computers.

With automatic computer algorithms such as the famous Douglas-Peucker algorithm for automatic reduction of the number of points required to represent a digitized line or its caricature [37], people started being able to use maps in ways that are not possible with paper maps. For example, people can zoom into more detailed areas, overlay data dynamically on top of the underlying map, automatically compare different maps/images taken at different times, etc.

Maps have come a long ways since clay tablets, however, most cartographers and geographers still use a single monitor for their tasks. At some point there is a threshold where only so much data can be shown intelligently and a geospatial visualization still be usable. After the display space has been used to its maximum capacity, it is logical that the next step should be to increase the size of the display. Once the display size has been increased more data can be added to the visualization.

Increasing the display size in effect increases the number of pixels that a visualization designer can use, thus allowing for more data to be shown at once. Several studies have shown a number of benefits with large displays such as performance improvements (e.g. [32]).

However, although large displays offer a variety of benefits it is unclear why large displays help and when. It appears that large displays help more with some tasks and data sets more than others. Intuitively, one might think that a larger display would always help with performance over a smaller display. However, research has shown that larger displays do not always improve performance for all tasks and datasets. Indeed, it appears that there are times when a smaller display affords the same performance time as larger displays [9].

This dissertation addresses the reasons when and why performance time improves with larger displays. Specifically, this dissertation focuses on one of the harder visualization topics: geospatial visualizations.

1.1 Definitions

Throughout this document it is imperative that the reader have a basic understanding of how I use certain terms. There are a number of terms that have multiple meaning or terms that are not common. These terms are defined here for better clarity of the document.

Resolution - The word resolution historically means the density of pixels on the screen, usually in terms of dots per inch (DPI) [20]. However, it is becoming common practice to refer to resolution as the number of pixels on a display, especially when people use the term "high-resolution displays." In this paper when the word resolution is used it refers to the common practice of referring to the number of pixels. So, a low-resolution display versus a high-resolution display means a low pixel count display versus a high pixel count display.

Scale - When used in this document the word scale refers to the zoom level, or magnification level, of the data. Specifically, we define scale from ranging from scale of 0.0 to 1.0. The scale, or zoom level, of 0.0 would show a magnification of 0% of the data while the scale, or zoom level, of 1.0 would show 100% of the data at full detail. Greater than 1.0 would enlarge the view without additional information.

In terms of geography, a zoom level of 1.0 would be the best level of detail that a map can provide. For example, the map used in the capstone experiment is 1 pixel for every 0.6 meters (1:1.9 feet). As this is the best level of detail provided, this becomes the zoom level of 1.0. A zoom level of 0.0 would the other extreme and would be a view of 1:∞ (infinity).

In other words, when one is looking at one's data at zoom $\text{level}_{1.0}$ then one can see all the detail of one's data. On the other hand zoom $\text{level}_{0.1}$ would show only a small overview, or possibly a small overview aggregation of the data.

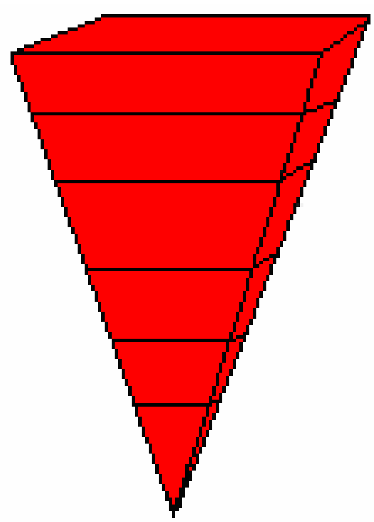


Figure 1. Example space-scale diagram. Lines indicate different zoom levels along the scale.

Consider Figure 1, an example space-scale diagram. If each level of the diagram represents a zoom level, then the base of the pyramid (i.e. the top of the diagram) would show all the details of the data at a zoom level of 1.0. The tip of the pyramid would show no data at zoom level 0.0 and would only show a small overview of the data at zoom level 0.99. More about scale will be explained when explaining the space-scale model in section Chapter 3.

Semantic zooming - As opposed to *geometric zooming*, semantic zooming changes the view, or sometimes the layout, of the data. The scale, or zoom level, is especially important with semantic zooming as what zoom $level_i$ one is at dictates what view one will see with semantic zooming.

For example, at zoom $level_{1.0}$ one might see all the detail about an object that one is visualizing. On the other hand, at zoom $level_{0.5}$ one might see only half the details of an object as the other details are not shown at higher zoom levels.

Semantic zooming does not show a continuous view of the data, like *geometric zooming*, but discrete views of the data. For instance, one might see one view of the data at zoom $level_{0.9}$ another at zoom $level_{0.7}$ another at zoom $level_{0.5}$ and so forth. When the view changes and what the view looks like is dependent on the visualization designer.

Semantic zooming is often used with abstract data and geospatial data. A common example of semantic zooming is the labeling in Google maps. At a country view only the states and major cities are shown. At a deeper scale smaller cities and town appear. This is often referred to as layering in geography terms.

Geometric zooming - As explained, geometric zooming is a continuous zooming that is usually based on a zooming algorithm. A common example of geometric zooming is the aerial and satellite images shown in hybrid mode of Google maps. Similar to how a person falling from space to Earth might view the terrain, the farther away the less detail but more overview one can see while the closer one is the more detail but less overview one can see.

Space - While scale is concerned about depth, space is concerned about breadth. In terms of geospatial views, space is the base or geographic area that one can see at a particular scale. Specifically, it is the total amount of area that the information takes up at the given zoom $level_i$.

Viewport – A viewport is some subset of the area of the space. It is fixed in size regardless of scale. As opposed to space whose area is defined by scale, the viewport size is constant.

If one maximizes the space of one's display, then the viewport size is the size of the display in terms of pixels. So, a display with one million pixels is said to have a larger viewport than a display with half a million pixels.

During the course of this paper, if different viewport sizes are discussed then it is inferred that the different viewports have the same pixel density. In terms of a coordinate system, a viewport is the window that a user sees and the space-scale diagram shows where in the model the person is looking.

Virtual navigation - Navigation is moving from one point to another in space and scale. Virtual navigation is when one is moving the viewport through the space and scale. This is accomplished by external devices, such as a mouse, that manipulate the underlying view.

Physical navigation - While virtual navigation changes the viewport, physical navigation moves where the user's physical eyes are looking. Any physical motion that affects the user's view, such as moving the eyes or head, walking, crouching, standing, sitting, ect. are all forms of physical navigation.

In general, the smaller the viewport size, the less physical navigation occurs; the larger the viewport size, the more physical navigation occurs. Intuitively, if one is working with a PDA then turning one's head will not help the user see more data as turning their head will move the eyes away from the view of the display. However, if one is using a 50-monitor tiled display, then turning one's head will be much more useful and performed more often.

Physical movement that does not attribute to a different view of the data is considered extraneous movement and is not considered physical navigation.

Zooming - Zooming is changing scale from zoom $level_i$ to zoom $level_j$ where $i \neq j$ and where $j \geq 0.0$ and $j \leq 1.0$. Zooming to a level less than 0.0 would show nothing. Zooming to a level greater than 1.0 would not show more detail, but would enlarge, or pixilate, the data which might be desirable at times.

When zooming with virtual navigation, one changes the zoom level of the viewport. Zooming with virtual navigation is discrete and is dependent on the underlying zooming algorithm. Semantic zooming is also affected in that if a zoom level passes certain thresholds then the view and often the amount of the data is changed.

When zooming with physical navigation then the viewport is not affected; only the position of the user (or position of the user's eyes) is affected. When "zooming in" the zoom level remains constant, but the person physically moves closer to the display. "Zooming out" is effectively moving away from the display.

Unlike zooming with virtual navigation, zooming out with physical navigation does not change the semantic view, but changes with visual aggregation due to visual acuity. In other words, if a person were to step back from a display then the equivalent of geometric zooming out is performed.

Panning - Panning is moving laterally in space. This can be achieved through virtual navigation or physical navigation (if the viewport size is large enough to accommodate such a physical navigation).

1.2 Approach

This dissertation was exploratory in nature. Although general research questions were asked in the beginning before any experiments were performed, each experiment led to a different set of questions which initiated the next experiment.

As a result, this dissertation explains a number of related studies that leads to a more conclusion capstone experiment. After the capstone experiment we synthesize the results of all the experiments into a concrete contribution.

1.3 Problem Statement

The problem that this dissertation addresses is:

What are the effects of large, high-resolution displays for geospatial information visualization?

Specifically, I want to know how human performance time and behavior are affected by large, high-resolution displays. I define performance time to be the time it takes for a person to perform a given task. By human behavior I mean outward observable physical behavior such as body movement that affects performance time.

However, that general question is a bit ambiguous. So this dissertation addresses how navigation, task scale, and performance are related to viewport size. By navigation we refer to physical and virtual navigation. Although people have to use their eyes to see data on a monitor, they must use their body to move their eyes.

Without any physical motion people cannot make out data on displays. People do not function in their environment without moving the rest of their body. As a minimum, head movement is required to comfortably see the entire extent of standard monitors.

With larger monitors people also make larger physical movements such as walking, sitting, crouching, etc. This additional physical movement allows them to see distant parts of the display with greater detail which leads to the question: How much additional physical movement would be observed with larger displays?

Virtual navigation is required to change the view of what is being shown on the display. However, with a larger display more details are shown at once and people can physically navigate more to see the additional details, therefore: How much more or less virtual navigation is observed?

Presuming different amounts of physical and virtual navigation with larger displays does this change help or hurt performance times? So, a first subset question is:

How do physical and virtual navigation interrelate with viewport size and performance?

As explained in section Chapter 1, different tasks, different datasets, also affect performance time. So, why do large displays help with performance more with some tasks than with others? As we are specifically interested in geospatial visualizations, the question becomes:

How does the scale of the task affect performance with viewport size?

Lastly, we are interested in how people approach their problems with larger displays. Do people use the same strategies on a small display as a large display? Are larger displays only more useful in that more data can be shown at once? So, the question is:

How are task completion strategies affected by viewport size?

1.4 Hypotheses

I first hypothesize that there will be different amounts of physical and virtual navigation. Related research shows that people can do better with larger displays (e.g. [32]). If people are able to perform better, then I hypothesize that different amounts of navigation are being performed for different display sizes.

I also hypothesize that as viewport size increases physical navigation will increase and virtual navigation will subsequently decrease until it becomes too fatiguing or uncomfortable to navigate physically. As people are able to use more of their body to see displays in a more natural way – closer to how people "see" the environment around them – they will naturally use more physical navigation. As more physical navigation is performed less virtual navigation will be required.

I further hypothesize that as the scale, or zoom level, of the task increases, and as the amount of data increases, the more impact larger displays will have. Intuitively, a small dataset with little information associated can be displayed just fine on a small display. On the other hand, a much larger dataset might be better suited for larger displays where all the data can be shown at once.

Lastly, I hypothesize that people will be able to generate better strategies that help them complete tasks faster on large displays. History shows that medieval battles were often won when the general was able to gain a larger overview of the battle site. Similarly, when people can see more details in greater context they are able to understand the "big picture" better. Understanding how the small pieces form the whole would help people have a better plan of attack for tasks.

1.5 Impact

The impact of the empirical experiments and the resulting model of this dissertation will help people understand the effects of large, high-resolution displays pertaining to geospatial visualizations. A greater understanding will be created to help specify the independent variables associated with optimizing performance.

Large displays have been shown to either decrease the time it takes to perform a single task or to perform more tasks in the same amount of allotted time. Understanding what factors impact performance will help with understanding what factors need to be manipulated and how to gain the optimal performance.

This dissertation delves into the causes of performance gains with large displays. By understanding the causes, both visualization designers and visualization users can benefit. This dissertation will directly help the fields of information visualization, ergonomics, human-computer interaction as well as people that use geospatial visualizations in their daily lives such as the intelligence community, cartographers, geographers, construction planners, military planners, etc.

Optimizing performance is different for different fields. For the business community it lowers costs. For military and intelligence communities it saves lives. For the common person it saves valuable time.

In addition, understanding how large displays affect people's behavior can have farther reaching consequences beyond geospatial visualizations. Much of the data collected in this dissertation can be used for other purposes such as multi-tasking and other types of visualizations.

1.6 Document Outline

This document will proceed as follows: related works, a number of important experiments that led up to my research question which include a basic perception and navigation experiment, navigating large maps experiment, real-time dynamic geospatial environment experiment, evaluation of viewport size and curvature experiment, the capstone experiment, and analysis of data.

Chapter 2 Related Work

A variety of studies have been performed on large displays and multiple displays to compare their effectiveness to that of small or single monitor displays. Figure 2 visually shows the different categories of research on different types of displays. In general, there are two independent variables that researchers look at: physical size of the display, and resolution (total number of pixels, not pixel density) of the display. For example, in one corner of the space are standard projectors, with a large physical size but below 1 mega-pixel resolution. Whereas, in the opposite corner is IBM's T221 22.2 inch flat panel LCD that contains 9.2 million pixels [70].

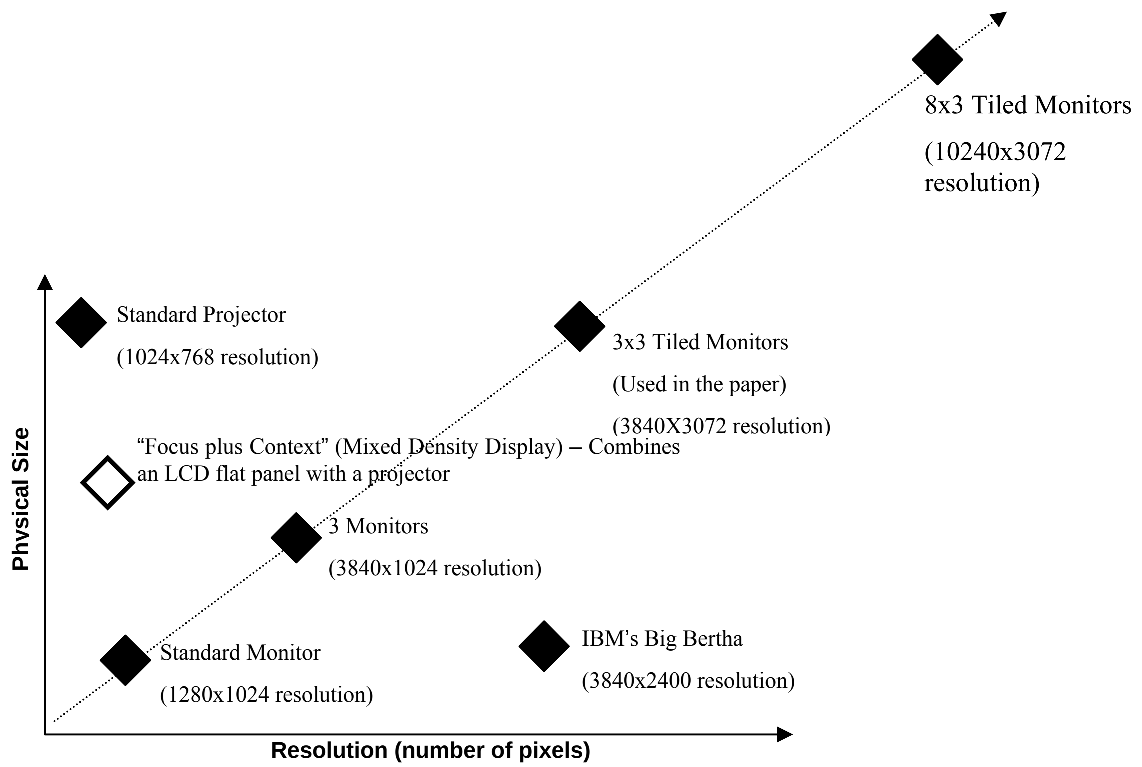


Figure 2. The configuration space of displays, showing how several instances relate to each other with respect to physical size and total resolution (number of pixels).

In this section, I will describe different display systems as well as pertinent research on displays. The reader should understand that there has been considerable work done in the areas of displays from virtual reality to perceptual psychology and that this section will only briefly touch on a few of the topics.

2.1 Standard Monitors

Multi-monitor (or "multimon" in other literature) is an increasingly popular configuration in businesses and homes to extend a standard desktop PC with more screen real estate. Modern operating systems such as Windows, Mac OS X and Linux offer plug-and-play capability, and dual-head video output is common on even a modest graphics card. With PCI® and PCI Express® SLI™ graphics cards, having multiple heads is also possible.

Multi-monitor configurations are easy to configure, without demanding expertise in computer science or related subjects.

Historically, Swaminathan and Sato [139] were some of the first researchers to report on the differences between single versus multiple monitors. They came to a number of conclusions that have since been validated by other researchers. Their most important contribution is that they point out that large displays are qualitatively different from single monitors. They explain that new interaction techniques and methods are needed to adapt to the larger displays.

Multi-monitor setups have since been receiving more attention in the research community. For example, bezel issues (i.e., edges of the tiles breaking up the continuity of the large tiled display) have been examined by Mackinaly [83] and Tan [140]. In general, bezels are a problem with maps, lines, network visualizations, and text, but can be handy in points of multi-tasking situations [8].

In addition, Polys, et al. [106] explain how information layout should differ based on screen size in information rich virtual spaces. His work lays a foundation on how small displays and large displays have different layout requirements due to physical size and additional screen real estate.

Usability issues of multi-monitor setups for multi-tasking have been explored. Hutchings [67], [68] [69] has indicated a number of windows management problems with larger displays such as pop-up windows, mouse control, and bezels. He explains a number of notification and navigation issues that do not exist with a single monitor but are prevalent with multiple monitors.

In addition, Terri Simmons [132] conducted a study comparing performance on different-sized monitors (17 inch to 21 inch), with slightly differing resolutions. His results were unsurprising in that they suggest that people perform faster with the largest monitor, and slightly higher resolution, as opposed to the smaller monitors.

It is clear that standard monitors when compared to larger displays are inherently different. This is one of the reasons why the research behind this dissertation is needed.

2.2 Standard Projectors

Several studies have suggested that the increase of the physical size of a screen helps with memory. Lin, et al. [82] suggests that an increase of one’s field of view increases one’s sense of presence and memory.

Tan et al. show how performance on a large low-resolution screen can be better than a conventional small screen even at the same resolution. They show that with the same visual angle participants in a study were able to perform better on a large screen compared to a single monitor for both spatial performance [144] and 3D virtual navigation [143]. However, large, low-resolution screens have the problem that they can only show the same amount of data as small screens because they have similar resolutions. As a result, the data on the screen is simply enlarged.

This dissertation does not specifically address projector displays, but it does address the issue of larger displays. As the sheer size of the display seems to affect presence, this work is relevant in understanding how people might be affected by display size.

2.3 Privacy Concerns

While larger displays afford improved performance they also allow an increase in privacy loss. Bishop and Welch documented an increase in privacy loss during their longitudinal study of replacing their own desks with large-screen projection displays [18]. They observed that visitors often treat information on their displays as being public. As the displays are so large, and the information readily available to read from a distance, information is “shared” with any visitor whether it be the intention of the user or not.

Tan and Czerwinski [141] explain that social convention dictates that people have “personal zones” and that information outside that zone is considered public. Also, objects on walls are considered public. Wall-sized projection screens are both. They also report the results of an experiment on privacy that shows that people are more likely to read sensitive material on a large display than on a small one.

2.4 Longitudinal Studies and Surveys

A few longitudinal studies have been performed on multiple monitors. Bishop and Welch [16] created a “desktop” environment that used projections on the wall to alleviate bezel and ergonomic issues. They used the environment for over a year. They report improvement in everyday work and an increase in physical interaction. Ball and North [8] performed a similar study but with multiple LCD monitors (see Figure 3) for a six month period of time with multiple users. They report a number of benefits in perceived increase in productivity and problems with bezels, adaptation to the display, and interaction problems.

Figure 3. Image of the display used in [1]for a longitudinal usability study.

Meredith Ringel [114] reported the results of a survey that she conducted among professional users of multiple monitors and professional users of virtual desktops. She reports the similarities and differences between having multiple monitors and having a virtual desktop. She includes a taxonomy of uses for the two types of displays. In a similar study, Jonathan Grudin [54] reports the results of a survey of professional users of multiple monitors and notes their transitions from a single monitor. He also includes common practices and uses for multiple monitors.

These studies are important in understanding how large displays affect people in the long term. Our own study ([8]) showed that people can use these displays over an extended period of time. This is important as it helps validate short-term studies: Short-term studies only show results from a short amount of time that may not be valid over a longer period of time. However, these longitudinal studies show that small gains over a short period of time become big gains over longer periods of time.

2.5 Two to Three Monitors

Czerwinski et al. [31] explain the current state of performance measurements and explain that their own study showed conclusively that participants using a multi-monitor configuration affording increased resolution (3 monitors wide) performed better than on a single monitor. Tan, et al. [145] also show how retention can be increased by using extra screen space to display different images in the user's periphery to help recall more from a particular task session using their prototype called Infocockpit. They account for this increase of retention due to the increase of presence. In addition to using 3 monitors, they also use a projector as a background to help memory retention.

Some studies have also shown that gender can have an effect with spatial performance. Some recent studies by Czerwinksi, Tan, and Robertson show that the effects of an increase of field of view can offset the gender bias [142][32]. Their findings indicate that women need a wider field of view than men to achieve the same performance.

These studies show a variety of benefits of a single larger display, or multiple monitor displays. This dissertation addresses why many of these benefits exist.

2.6 Mixed Density Displays

In a unique study, Baudisch et al. [12] performed an experiment using their "Focus plus Context" screen to study the effects of having a small LCD screen embedded within a large projection screen (both standard low-resolution). In effect, they created a focus+context visualization using pixel density distortion instead of spatial distortion. They conclusively showed that participants were able to perform better while using their mixed-density display than with standard monitors and a variety of navigation strategies.

Similarly, but with a different twist, Ashdown, et al. [4] created a mixed density display for the desk. By combining a number of different projectors from different angles they were able to have different pixel densities at different areas of the desk with the highest density of pixels in the middle of the desk. They explain that their system is extensible and easily constructed.

This dissertation is different from the mixed density displays in that it presumes a mobile person. A mixed density display is most effective for stationary people that do not move. By presuming a mobile person, we keep a constant density so that a person can have the highest pixel density available at any particular time.

2.7 Curved Displays

Researchers have also constructed a projection-based multi-monitor display at Microsoft. Starkweather et al. [134][31] created a curved desktop called DSHARP using DLP projectors and parabolic mirrors. This display creates a curved environment for users to use as they would their primary desktop.

Shupp, et al. [131] created a reconfigurable display out of LCD monitors that can be curved horizontally at any angle (see Figure 4.b). This is achieved by creating autonomous stands that can be moved independently of each other. Shupp reports the results of an experiment that shows that curving the display around the user, versus having it flat, always helped users with performance for the tasks performed. This is the fourth study experiment that we performed (see Chapter 8).

2.8 CAVE and Derivatives

Among the first large-format display systems to receive widespread use was the CAVE™ (CAVE Automatic Virtual Environment), a projection-based *Virtual Reality (VR)* system that surrounds viewers in an immersive environment with four or more large display walls.

A CAVE system typically arranges four 10 ft X 10 ft screens in a cube made up of three rear-projection screens for walls and a front projection screen for the floor [30]. Five-wall [160] and six-wall configurations [120] exist as well, but they require special screens that can support the weight of users and/or movable screens to enable entry into the facility. One concern with constructing CAVE systems is the space for the optical path between projectors and screens. Most implementations fold each optical path with at least one mirror in order to shrink the footprint of the total system. Typically, all users wear stereo shutter glasses and one user wears a head tracker with six degrees of freedom (DOF). This enables all users to see stereo imagery, although only the tracked user will have a correct perspective projection. Tracked 3D input devices afford multiple DOF interaction; data gloves and joysticks are commonly employed in immersive virtual environments.

Often a CAVE™ is used to increase the idea of immersion for a given virtual environment. How the idea of immersion affects one's cognitive abilities is being thoroughly researched. Raja, et al. [109] suggests benefits of being surrounded by large low-resolution screens (CAVE) when dealing with data visualization (information visualization). They suggest that an increase of immersion leads to better performance. For a background overview of immersion, the reader might consult the following preliminary work: [11][128].

The work done with CAVEs has been especially relevant in helping us to understand immersion and physical navigation. The capstone experiment and analysis are reliant upon understanding physical navigation. Without the background research performed with CAVEs, some of the conclusions that this dissertation claims could not be made.

2.9 Large Tiled Displays

Tiled LCD panels are sets of LCD displays arranged in a 2D array. The array can be arranged flat like a wall display (see Figure 4.a), flat like a table, curved (see Figure 4.b), or in other configurations. The combined pixel count across the arrays can reach into the 100 million pixel range. For example, the Electronic Visualization Laboratory, University of Illinois (EVL-UIC) has developed a large 100 MPixel display called LambdaVision

[113] and NASA has developed the Hyperwall which contains 49 LCD panels tiled in a 7x7 array [125]. Some advantages for tiled LCD panels are: They are easier to align and color correct than projectors; they are less expensive than projectors, which use expensive bulbs with relatively short lifetimes; they take less space (no throw distance needed).

A disadvantage is the array has borders between each tile. The large tiled LCD panel displays offer a variety of uses due to their high pixel counts. Ultra-high resolution imagery such as geospatial data can be shown (and interacted with) in one contiguous display. Multiple display content (e.g., graphics, desktop content, video, and imagery) can be displayed all at once on different parts of the display.

Figure 4. a) Example display wall. b) Example power desktop (curved display wall).

EVL-UIC has developed a table-top tiled LCD display called the LambdaTable [77]. The advantage of the table-top format is that it is familiar to many users who prefer a sandbox as a metaphor: every user can see the physical shape in a sandbox and can move to a location to modify the surface. The tangible nature of the interaction with the data is a big advantage. The table-top nature makes the system practical for many users to collaborate in an application.

Previous research in large tiled displays allowed us to create our own displays. Without such research pushing the envelope of display technology it is possible that we would not have been able to create our displays.

2.10 Projector Arrays

Projector arrays can consist of CRT, light-valve, or LCD projectors. CRT projectors provide the most flexibility in terms of geometry control, but have limited size and brightness constraints. The light-valve projectors are bright and very flexible for expanding the overall size of the array. Since several light-valve imaging schemes are driven by scanning CRTs, they also have good geometry controls for the output image. LCD projectors offer a cost-effective, low maintenance solution for arrayed projection; however, they have virtually no geometry controls.

Projector arrays are becoming popular due to their lack of bezels and the constantly-improving seamless integration of multiple tiles. A large amount of research has been done in the area of perfecting both the overall resultant display and the rendering algorithms. For example, research has been performed on color gamut matching [157], seams [137], misalignment [61][28], luminance matching [86][2], and image blending [63]. Projectors also offer what CRT-based, LCD-based, and plasma monitors do not: a separation between the device size and the size of the displayed image.

A small projector can be used to create a very large display or to create a very small display. The possible range of image size is limited by lumens, lens configurations, and available space. The resolution of the projectors, continually improving, is also a factor to consider. The highest resolution projection technology we are aware of is Sony's high resolution liquid crystal device, Sony 4K SXRD [133], which can produce an image resolution of 4096 X 2160. The technology will be used in high-end projectors. Additionally, arbitrary physical shapes can be used as the display surface. The result is that projector arrays enable reconfigurable and flexible display designs with (theoretically) little bezel distortion [110] and [162].

Projector arrays' potential for large images also allows for large group meetings with data displayable to the entire audience. Fitzmaurice, et al. [48] explain a large group meeting room called VizStudio. They explain a number of business applications of projector arrays. They especially highlight things such as first business impressions to clients, ability to do better virtual design, and ability to work in groups effectively.

2.11 Stereoscopic Displays

Stereoscopic displays show two sets of pixels for an image, making one set visible to the user's left eye and the other to the right eye. Typically the user is required to wear special glasses or viewing aids to see the 3D effects. However, a recent development, autostereoscopic displays, eliminates the need for special glasses. High-resolution stereoscopic displays are typically physically larger than their low-resolution counterparts and must account for the following factors: (1) larger space for head tracking (recommended to properly view the 3D effects) and (2) larger number of pixels to be displayed (twice as many). These factors are especially important if the user desires to interact in real-time, operate closely to the display surface, and move around the space in front of the display.

For example, EVL-UIC has developed an autostereoscopic display called Varrier™ [123], which does not require users to wear any stereo glasses to view the 3D effects. Their approach involves a curved LCD tiled display with a parallax barrier affixed to the front. The user is free to move within an area of approximately 32 in X 48 in (81.3 cm X121.9 cm). In addition, Liao et al. [81] have developed a high-resolution display using Integral Videography technology and 9 XGA projectors arranged in a 3 X 3 array, leading to a total resolution of 2872 X 2150 pixels. Their system generates geometrically accurate high-quality autostereoscopic images, and reproduces motion parallax in 3D space without any special viewing glasses and head trackers.

Another innovative high-resolution stereoscopic display is the Dvision from Tokyo Institute of Technology [56]. D-vision uses 24 projectors to provide stereoscopic projections on a hybrid screen. A combination of rear and front projection provides high-resolution in the flat central region in front of the user and lower resolution on curved screens around the periphery. For more information on the subject, see [96].

2.12 Software Toolkits

Raffin and Soares [107] present a review of common software toolkits supporting PC clusters for Virtual Reality systems, including CAVELib, VR Juggler, Syzygy, OpenSG, Chromium, and others. Although they discuss distributed rendering software in the context of VR and parallelism, these tools are naturally applicable to large high-resolution display systems. For example, Chromium [29][66] has been widely used to support interactive parallel visualization applications displaying to tiled displays. OpenSG [155] implements rendering on tiled displays by dividing the screen into $M X N$ uniformly spaced tiles with a render server assigned to each of them.

Typical X-Windows servers provide support for multiple displays connected to the same machine via the Xinerama extension. The DMX project [36] provides a proxy X server that is a front end to X servers running on each rendering node in a cluster. The X client application will connect to the front end server; rendering requests will be broken down as needed and sent to the appropriate back-end servers via X11 library calls. DMX is transparent to the application and supports standard mouse and keyboard input through the XInput extension.

Both DMX and Chromium were used extensively in the last two experiments in this dissertation. Previous work to Chromium, such as WireGL, have led to innovations that made this dissertation possible. Without the previous research performed with such applications at DMX and Chromium, large tiled displays would not be feasible.

2.13 Perception

A great deal of work has been performed in the areas of perception and perceptual psychology. I will only touch on a few. One of the most noteworthy researchers in perceptual psychology is Anne Treisman. Her work has focused on understanding basic perceptual characteristics such as preattentive perceptual processing. For example, her work on implicit coding without attention for novel shapes [34], conjunction search [150], visual search [149], memory for visual patterns [92], orientation and size features of visual phenomena [26], and basic perception [147] to name a few. Her work has been one of the central pushes behind “preattentive processing” and visual “pop outs.” Other researchers have continued the research of perception, such as [72], [58], [158], and [39].

Treisman’s work, and the work of her co-researchers, has laid a foundation of perceptual work that allowed information visualization researchers to work with. In effect, by discovering concepts such as preattentive processing, Treisman helped the field of information visualization become more efficient in expressing the patterns of the underlying data. However, little work has been done to see how far her results extend to large displays and large fields of view.

2.14 Working Memory

The way people can retain and recall things has long been a study in cognitive psychology. Working memory is a theoretical framework that refers to structures and processes used for temporarily storing and manipulating information. Working memory is now the more common term used in cognitive psychology used more prevalently over the term “short-term memory.” The emphasis is not on manipulation and work rather than simply a smaller store than long-term memory.

Miller's well-known paper explains that people are only able to keep seven, plus or minus two chunks, or objects, in working memory at a time [90]. It appears however that the amount of chunks depends more on the type and length of the chunks, such as words or numbers, rather than the number of chunks [5][6].

Working memory plays an important role in how well participants were able to retain information for the different experiments presented in this dissertation. The better participants were able to recall information, the better they were able to perform their tasks.

2.15 Fitts' Law

Fitts' law is a model of human movement, predicting the time required to rapidly move from a starting position to a final target area, as a function of the distance to the target and the size of the target. Fitts' law is used to model the act of pointing originally published by Paul Fitts in 1954 [46] with further details in 1964 [47].

Mathematically, Fitts' law has been formulated in several different ways. However the most common approach is as follows:

$$T = a + b\log_2\left(\frac{D}{W} + 1\right)$$

where

- **T** is the average time taken to complete the movement. (MT is sometimes used to mean movement time.)
- **a** and **b** are empirical constants, and can be determined by fitting a straight line to measured data.
- **D** is the distance from the starting point to the center of the target.
- **W** is the width of the target measured along the axis of motion.

Basically, there is a speed/accuracy tradeoff associated with pointing, where targets that are smaller and/or further away require more time to acquire. On the other hand, larger and/or closer by require less time to acquire.

2.16 Interaction

As more studies show the usefulness of large displays, different interactive techniques have followed. A number of different types of techniques, from using less traditional input techniques to different ways of interacting with the mouse have been developed. Large displays and multiple monitor displays are inherently different from smaller displays and logically should be interacted differently.

A large amount of research has been done on pen-based interaction. For example, Tivoli [40], Flatland [85], and Fluid Interaction [55] are all well-known examples. These techniques have historically been used for white-board type interactions.

Rekimoto [112] created an approach of using digital whiteboards by enhancing the pen to have a range of functionality based on a hand-held device that is used similarly to a color palette that oil painters use. By choosing what functionality the pen should have based on the hand-held device allows users to have a larger range of custom functionality. Myers [93] implemented a similar system but for use with standard PC's.

The Interactive Workspaces Project [71] explored interface possibilities for people working together using large displays. They integrated a variety of interaction devices and techniques including wireless multimodal devices.

Other well-known interaction techniques also exist, such as laser pointers (e.g. [100]) and head-tracking (e.g. [1] and [16]). A range of techniques have also been created for facilitating users in accessing objects physically far from them on large displays using various software techniques (e.g. [52], [13], [53], [101], and [75]).

A taxonomy of logical input devices cast in the human perspective can be seen in [50]. This taxonomy was extended by Buxton in terms of states [22]. The idea is that any interactive device fits a certain purpose, or purposes, and that any particular device must be in a particular state at any one time.

Mouse-based interactions have also been developed. Of particular note is the high-density cursor by Baudisch, et al. that focus on a greater visibility of the mouse cursor [14]. Benko, et al. introduced the concept of cursor warping [16]. Cursor warping is the act of instantly jumping (moving) the position of the cursor from one monitor to another. Wallace, et al. created a multi-cursor X window manager at the systems level [146]. Their contributions differ from other cursor ideas in that they implemented their cursor at the desktop level instead of a single application. In addition, research has been performed on cursor orientation and how it affects performance [105].

Hand gestures as an interactive technique have also been researched extensively. For example, LaViola et al. [71] developed a set of novel input devices for CAVE-based virtual environments. They employ hand gestures, such as pointing with a tracked, finger-worn sleeve or foot gestures, such a tapping toes or heels on a map with a foot-worn slipper for navigation. They enable object selection with flexing and pinching while wearing a glove with buttons added to engage actions. Similar user actions can be measured by computer vision systems [75]. Malik et al. [87] use multi-hand gestures to enable the user to control an object and the workspace simultaneously, thus allowing the user to bridge the distance between objects, or to offer the user a wider range of gestures by allowing the two hands to work together. They activate widgets under the hands to similarly add to the power of gesture-based interactions. Vogel et al. [151] use hand gestures to indicate typical user interface actions such as point-and-click when working at a distance from the display surface. In order to achieve a stable pointing operation, they filter the detected finger position. Other well-known gesture-based approaches include [79] [23]. Nickel and Stiefelhagen [99] use gestures in conjunction with head gaze to accurately interact with large displays.

Touch screens and camera-based touch gestures have also been implemented with large displays. For example, Ringel, et al. [115] and Matsushita, et al. [89] have each implemented an interactive display that takes advantage of human touch.

Khan, et al. [75] created an interface for physically larger displays that allows a user to see through a "telescope," similar to a porthole, to another part of the display. The user then can manipulate the other part of the display through the telescope similar to remote computing.

In addition, Microsoft Research has been active in the area of interaction for large displays. Their work can be summarized in [117].

As will be shown, the effectiveness of the interactive techniques and devices used with large displays is important in understanding performance curves. It will be explained that the less an interactive device confines a person to a particular place or location, the more a person is able to move around. It will be shown that this freedom is imperative for better performance on larger displays.

2.17 Embodied Interaction

Embodied interaction is the idea that the cognitive mind is not separated from the physical body. Exploiting this idea involves using the body's already usable functionality to enhance performance and insight in tasks. Embodied interaction makes better use of physical embodied resources such as motor memory, peripheral vision, focal attention, and spatial memory [38].

Humans are embodied beings. The embodied interaction approach emphasizes the role of bodily reality in the creation of meaning, which constitutes the essence of thought and experience. When people speak, for example, their heads, eyes, bodies, arms, hands, and face are engaged. It reveals how people use resources of our body-space to organize our thoughts, keep context, index our ideas, and situate/ shape our mental imagery out of which our talk flows. People's capacity for spatial memory, situated attention, and motor activity fuels these embodied resources.

With small displays many of the body's built-in functionality, such as peripheral vision, are wasted. Gone is the ability to see movement in the periphery or to maximize spatial memory. Spatial memory has been shown to be a highly effective as a tool for categorization and memory. Several examples that use spatial memory in a virtual environment include Robertson, et al.'s Data Mountain [118], Mackinlay, et al.'s Information Visualizer [84] and Robertson, et al.'s 3D Window Manager [119].

The idea that a head mounted display might be better than a single display is based on the very idea that people are able to use spatial memory based on their body. The idea is that people are able to use proprioception, the unconscious perception of movement and spatial orientation within the body, to remember where objects are in a 3D environment. Large data sets often require some form of navigation to understand a visualization.

When the user's viewpoint does not encompass the data domain in its entirety, virtual navigation is required [33]. Being unable to see all of the data at once, the user is forced to integrate the information shown on the display into a mental representation often called a cognitive map. The user then must use their cognitive map to navigate the data to gain insight [121]. This can be problematic for two reasons. First, instead of using one's cognitive resources to understand the data, much of the time is spent navigating the data. Second, such cognitive maps are often incorrect and rely on landmarks, particular patterns or pieces of data, to create a distorted cognitive map [151], [159].

Real environments typically do not represent data. As a result, navigating in a virtual environment to better understand one's data demands greater accuracy of the user's cognitive map than do real environments [153]. The motor, peripheral vision, and proprioceptive cues that come from walking and turning one's body and head that help in forming a cognitive map are often absent from small display environments [122].

These bodily senses or functions that people have will be used as a basis for why physical navigation is preferred by participants and why it results in better performance times. Knowing that people are designed for a 3-dimensional world helps explain why people are able to perform so much better on large displays than smaller displays.

2.18 Related Works Summary

Large displays take advantage of a number of elements of human behavior and abilities. From the many varied areas of research of perception to interactive devices to cluster software toolkits, the work in this dissertation would not be possible.

The first law of geography according to Waldo Tobler is that "Everything is related to everything else, but near things are more related to each other" [147]. In summary, it appears that as large displays touch on human behavior in all its forms from perception to ergonomics and large displays also touch on complex algorithms that there a many areas of work that are related. As a result, I have only mentioned a few of the more relevant areas research that are related to my dissertation.

Chapter 3 Expanding the Space-Scale Model

This section expands upon the basic space-scale model from Furnas and Bederson [51]. Specifically, it expands the ideas of space and scale to include the idea of a changing viewport size and the idea of a difference in behavior between physical and virtual navigation.

3.1 Overview versus Detail

When dealing with large amounts of data people are often concerned with different scales of that data from various perspectives and scales [164]. For example, one person might be concerned with the general overview of a data set while another person might be concerned with only certain detailed parts of the data. When navigating through these different scales, one is navigating through what has become known as space scale [51].

In space scale there exists a tradeoff of overview versus details as viewport size increases. Overview can be defined either in terms of area or objects visualized. In terms of area, overview is the amount of space one can see at once. For example, a map of Washington, D.C. is a smaller overview than a map of the United States. The further one is able to zoom out, the more of an overview one is able to see. In terms of objects, overview is the number of objects one can see, whether aggregated or not.

Details are pieces that form part of the whole. A detail can be an attribute or piece of information. Details about a map might include the name of cities or roads. As one zooms out one cannot see as much detail and small roads might disappear.

To generalize the idea, if the viewport size decreases then either detail, overview, or a combination of detail and overview must decrease as well. On the other hand, if the viewport size increases the opposite must happen. Figure 5 shows a visual representation of how viewport is associated with detail and overview. For example, if one condition is increased, say detail, then either viewport must be increased to maintain the same overview, or less overview will be shown if the viewport is maintained.

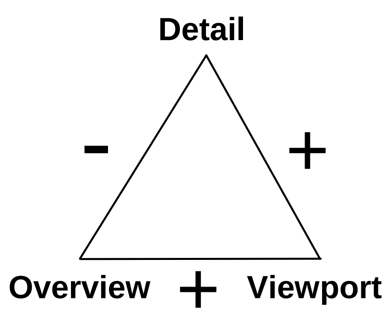


Figure 5. Visual representation on how viewport, overview, and detail relate.

As another example, consider Figure 6 and Figure 7. Figure 6 shows the amount of overview and details one might see on a smaller viewport size. Supposing one were to increase the number of pixels of the display to a larger viewport size then one would have three choices. The first choice would be to simply increase the overview while maintaining the detail density (amount of detail per pixel). By doing this one could see more of the map at once without any additional detail clarity (see Figure 7.a). The second choice is to increase detail density while keeping the same overview area. By keeping the same overview one can see more detail of the same area of the map (see Figure 7.b). The third choice is to increase both overview and detail density. However, one does not get as much overview as the first choice nor as much detail as the second choice.

Figure 6. Part of a map shown on a small viewport size.

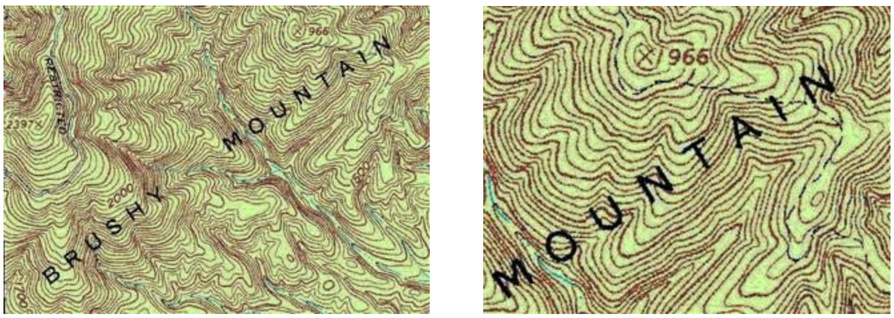


Figure 7. A larger viewport size than Figure 6 but with either more overview (left) or with more detail (right).

Space-scale diagrams are analytical diagrams that help understand multi-scaled data [51]. Scales, as defined in section 1.1, are different magnifications of the data; different degrees of detail. Space, also defined in section 1.1, is the area where certain amount of details can be seen at a particular scale; the deeper the scale, the more details one can see and the larger the space.

Figure 8 shows how the relationship can be applied to the space-scale diagram [51] with a constant viewport size. The left image of the map shows a certain amount of overview of the data. As one zooms into a deeper scale (the image on the right) one loses more of the overview. One cannot maintain the same amount of overview while increasing scale with a constant viewport size. This is true even with the use of information visualization techniques, such as focus plus context. In order to increase both space and scale one must increase the viewport size.

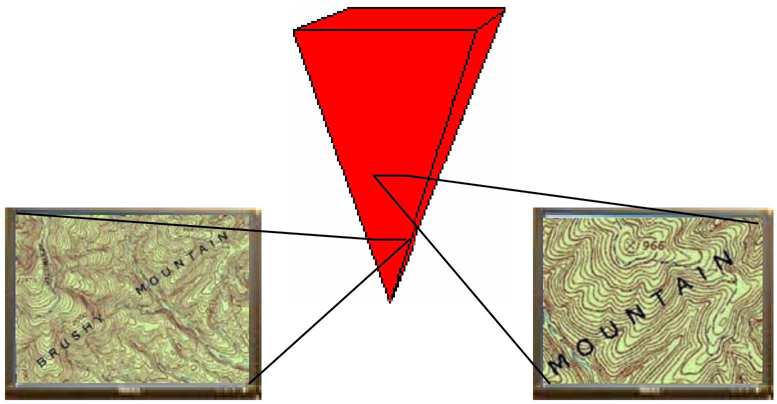


Figure 8. Space-scale diagram showing greater overview (left) and greater detail (right).

The space-scale diagram as created by Furnas and Bederson [51] is an upside down pyramid. The base of the pyramid (the top) is where all details of the data are shown at zoom level$_{1.0}$. The point of the pyramid (the bottom) is where no details of the data are shown at zoom level$_{0.0}$.

In order to increase both detail and overview one must increase the viewport size (see Figure 5). Figure 9 shows two different space-scale diagrams that each show the area covered by a display. The space-scale diagram on the right shows the maximum overview/detail area provided by the given viewport size. At any point in the white area in the diagram a person can see a maximum overview/detail ratio. In other words, given the maximum detail a person can only see a limited amount of overview or given the maximum overview a person can only see a limited amount of detail.

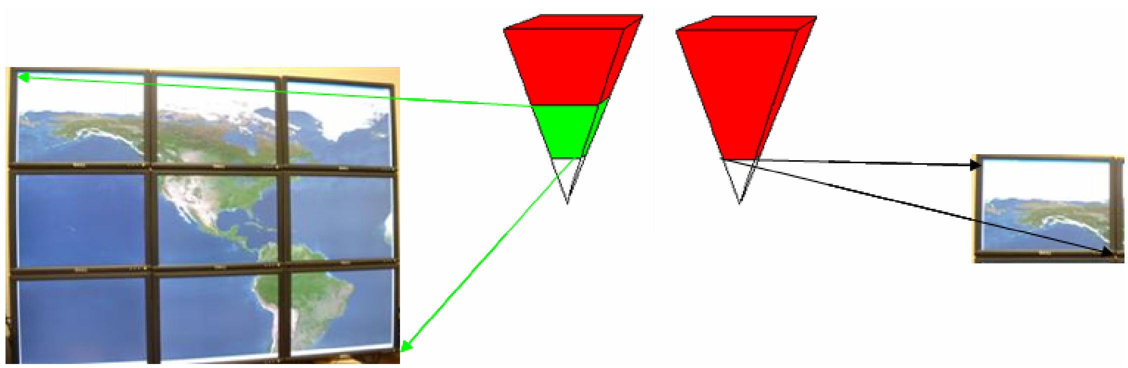


Figure 9. Augmented space-scale diagram augmented to showing how a larger display, a display with more pixels, can show more overview and details than a smaller display.

The red areas represent the area that exceeds the overview/detail ratio for the given viewport size. For the viewport size shown on the right, the red area is either more of the overview (the rest of the planet Earth) at the same detail level, or more detail with the same amount, or more, overview. If a display were of sufficient size to display all the overview with all the detail at once then there would not be a red area for that viewport size.

The space-scale diagram on the left shows the additional area that a larger display covers in green. For example, the larger display on the left is able to show an overview of all of

North America and two-thirds of South America in full detail. However, the smaller display on the right is only able to show Alaska at full detail.

As explained in Figure 5, instead of showing the maximum detail, Figure 9 could show the maximum overview. For either display size, each display would show an overview of Earth. However, the larger display would show an image of Earth with far more clarity, detail, than the smaller display.

3.2 Space-Scale Navigation

3.2.1 Panning and Zooming

If one augments the space-scale model with physical navigation, then one is able to *physically* zoom and pan in space scale as well. Figure 10 shows two space-scale models that are augmented with physical navigation. In the model there is a black line that represents the current viewport of the data. Based on that viewport one is able to see the area in blue. One must virtually navigate to change the viewport to see the areas in red.

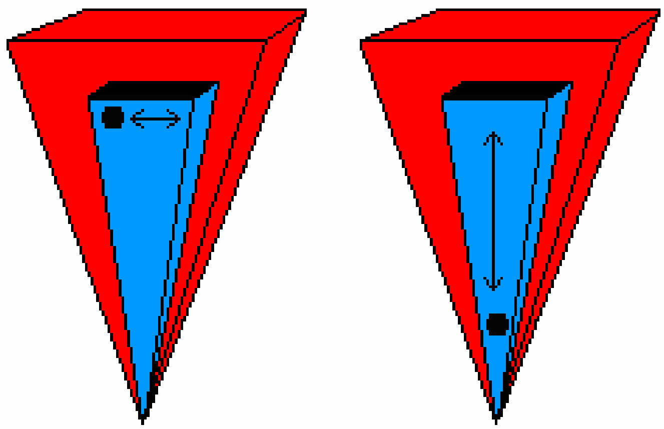


Figure 10. Two space-scale models augmented with physical navigation. The left model shows how a person (depicted as a black dot) can physically pan. The right model shows how a person can physically zoom.

3.2.1.1 Panning

In Figure 10 the model on the left shows a black dot that represents a person in 3D space. This person is able to physically "pan" by moving parallel to the display. The right model shows a person that is able to physically "zoom" by physically getting closer or further away from the display. The blue area of physical navigation is *within* the virtual navigation space. As long as one is interested in only the data represented in that area, no virtual navigation is required.

An example of someone physically panning is moving from one point of the display to another point while maintaining the same distance away from the display. This could be accomplished by moving the head or physically moving the body such as walking to another part of the display.

Physical panning is similar to virtual panning in that a person does not change the zoom level, but is able to see different data in the same space. However, the difference between virtual panning and physical panning is that physical panning does not change the view.

One can only look at what is currently being shown on the display. Virtual panning actually changes the view by virtually moving the viewport.

The larger the viewport the more one is able to examine the space with physical navigation and the less virtual navigation may be required. For instance, if the space is smaller than the viewport size then virtual navigation is not required. If the space is larger than the viewport then virtual navigation is required to view the entire space.

3.2.1.2 Zooming

Physical zooming and virtual zooming are fundamentally different from each other. Physical zooming consists of visual aggregation, visual acuity, and visual perception; the farther from the display, the more different the view. Virtual zooming is usually performed at a constant physical distance and manipulates the viewport zoom level. By changing the zoom level semantic zooming is affected.

In geographic terms, there is a base view and a thematic view. The base view is the geographic view that is used as reference and is not aggregated. The thematic view is the view of visualized objects.

What is included in the thematic view and the base view differs from visualization to visualization. However, the main difference is that the vase view is never aggregated when zooming. It might change, such as showing fewer or greater details through graphics algorithms (such as removing every third pixel when zooming out), such as seen in Figure 8, but the details themselves are not aggregated in a visualization context.

In general, there are three different semantic zooming approaches (for thematic views) for geospatial visualizations:

1. **Hierarchical**: This is defined as a hierarchy of information being visualized. This hierarchy can be defined as going from largest, or most important, to smallest, or least important. An example is a world map. When the world is shown then generally only the names of countries are labeled. As one zooms in, smaller items, such as states, and large cities appear. Counties and medium-sized cities might appear next. Lastly, towns and villages might appear at the lowest level.
2. **Non-hierarchical, not able (or not desired) to be aggregated**: This is defined as a set of individual objects being visualized without any object having more importance than another where it does not make sense to aggregate, such as average, the attributes of the objects. For example, on a traffic map that has heterogeneous data, such as cars, people, and buildings, it is not logical to aggregate the three types of objects together. It might make sense to aggregate the individual object types, such as showing only how many people are in a square mile of a city. However, it is not logical to aggregate heterogeneous data such as people and buildings together.
3. **Non-hierarchical, able to be aggregated**: This is defined as a set of individual objects being visualized without any object having more importance than another where it makes sense to aggregate, such as average, the attributes of the objects. For example, if one were looking at houses for sale in a particular area it might make sense to aggregate the prices of the houses together in a logical way. For

instance, at the lowest zoom level all the houses are displayed individually without any aggregation. However, at a higher zoom level the houses might be aggregated to display only one house indicating the average price for a particular region at a particular zoom level such as at the subdivision level, city level, state level, or the country level.

There are also a number of types of aggregation techniques.

1. **Mathematical**: One or more object attributes are averaged, the total numbers of objects being presented are counted, or other similar mathematical aggregations.
2. **More or less**: At each zoom level more, or less, information is presented. For example, if one is going from a higher zoom level to a lower zoom level then at each semantic threshold (based on zoom level) another attribute is displayed. Similarly, instead of more attributes, more data on each attributed is presented. The reverse is true when going from a low zoom level to a higher zoom level.
3. **Combination**: A combination of the previous aggregation types is used.

I refer to the above aggregation techniques as *computational aggregation* as they were computed by a computer. Computational aggregation is a common technique for understanding large datasets on smaller displays.

Visual aggregation on the other hand is aggregation that one performs with physical eyes. For example, if one were looking at a geospatial visualization and stands back, zooms out via physical navigation, then one is not able to see as much detail and visually aggregates the details with physical eyes and brain.

Visual aggregation is helpful in finding the trends, or patterns, of data at a detailed level. As people are able to see all of the details for a particular zoom level they are able to more fully see all the detail at once and mentally aggregate the data themselves.

However, visual aggregation introduces problems of color aggregation, visual distortions, etc. For example, if color is meaningful to a geospatial visualization then colors that are not present may appear when the user is physically distant from the display. A series of blue and yellow color placed close together may appear to be one color that is neither blue or yellow ten feet away from the display. This non-present color may indicate to the user a value that does not exist in the underlying data. For more information on visual distortions see [158] and [42].

Expert mapmakers are able to take color distortion into account. For example, on my wall I have a map of all of Washington, D.C. Standing back at five feet one can only see the large labels that indicate where the boundaries are and what the counties are called. Standing closer one can see more details that include the major highways. The closer one looks the more details are present until one can see the names of all the roads in Washington, D.C.

Computational aggregation is helpful in getting precise overview statistics such as finding out what the exact average price for all the houses are in the United States. Also, it is helpful in hiding non-relevant details. For example, computational aggregation can be helpful in hiding unnecessary details that are not important at the time such as showing all the streets and roads in the United States when one is only interested at the state level.

However, computational aggregation has two drawbacks. First, finding out what the average price for all houses are in the United States falls away from the reason of information visualization: one can query a database and find the same answer. One cannot query a database to find the trends and patterns that one sees with visual aggregation. Second, sometimes it is best not to hide information. Often one does not know what details are missing and as a result misinterpretations or misunderstanding can occur.

In summary, physical zooming causes visual aggregation which allows people to see more patterns and trends but may lead to visual distortions if the visualization is not created correctly. Virtual zooming causes computational aggregation and is helpful in showing precise overviews and hiding irrelevant data.

3.3 Physical/Virtual Tradeoff

In addition to a space and scale tradeoff there exists a physical navigation to virtual navigation tradeoff as well. Figure 11 shows two example space-scale diagrams. The left image represents a smaller display than the right image.

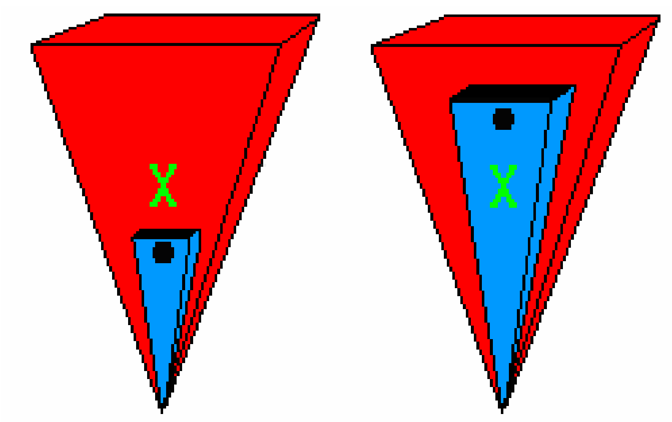


Figure 11. Two images showing the same target in the space scale. The green "X" indicates the target that one is interested in.

On each diagram there is a destination data point, or target, indicated by a green "X." In order to access the target at that point on the smaller display (the image on the left) one must virtually navigate (e.g. zoom in). However, for the larger display one is given an option to physically navigate (e.g. stand back), to virtually navigate (e.g. zoom out), or both (e.g. stand back a little and zoom out).

If the desired target is in the blue area then a person is given the option to physically navigate, virtually navigate, or a combination of both. On the other hand, if the desired target is *not* in the area covered by the display, then virtual navigation is required.

So, if the green "X" is within the blue area the user may decide to physically or virtually zoom. This tradeoff allows the person to decide between visual or computational aggregation. If physical zooming is chosen then a more complete mental mapping may be created of the green "X" with the details surrounding it. On the other hand, if virtual zooming is chosen then more detail may be hidden as the user focuses in on the green "X" at the desired zoom level.

In addition, performance time may be affected. Standing back may be quicker if the person is already standing, but may be much slower if sitting. Also, the dataset may be large and a certain amount of computing time must be given to change to view to correct zoom level. This can be a non-trivial computation involving mathematical aggregation.

In summary, the larger display on the right of Figure 11 allows a tradeoff, or choice, where the smaller display on the left does not. In addition, the larger display on the right allows a person to perform both virtual and physical zooming to get different perspectives of the data which is impossible with the smaller display on the left.

3.4 Perception and Navigation

In terms of information visualization, navigation is nothing more than information access. In other words, it is the effort extended by a person to get to a point in space scale where they can perceive the desired data. Navigation in space scale is a combination of physical and virtual navigation.

Perception and navigation are not independent of each other. A person cannot perceive visual data without their physical eyes. Nor can a person simply look straight ahead without eye or neck movement for maximum performance.

In summary:

1. Large displays allow more data to be shown at once allowing for greater potential visual perception; a greater amount of data can be seen and more perceived at once.
2. Large displays allow users to have larger visual aggregations of their data through physical zooming. This visual aggregation allows for different perspectives that may not be possible with smaller displays.
3. Larger displays allow for a choice of virtual or physical navigation. This choice affords an opportunity for users to improve their performance times by choosing between which navigation will allow the best results for their tasks.
4. Together, with users being able to perceive more data and choose between virtual and physical navigation, they are able to perform their tasks faster with potentially more insight into their data.

Chapter 4 Hardware and Software Used

For the different experiments we used two different hardware and software architectures. For all but the last two experiments explained in this dissertation we used a Windows-based computer with nine tiled monitors. The last two experiments used a twenty-four monitor display cluster with twelve GNU/Linux computers.

4.1 Windows Machine – 9 Monitors

In order for the single machine to power all nine monitors we used five dual-head graphics cards with the last graphics card using only one port. Figure 12 shows two images of the machine used. The left image shows a close-up picture of the monitor cables connected to the computer. The right image shows a zoomed out picture showing a better context of the computer, cables, and monitors.

Figure 12. Example of what the graphics cards and cables looked like from the back of the computer powering the nine-monitor display.

We also constructed a wooden stand to support the tiled monitors. Figure 13 shows two pictures of the stand with the monitors. The image on the left shows how the monitors appeared with one monitor sitting on the computer to show the underlying wooden frame. The image on the right shows the monitor stand from the side to show a better view of how the monitors were supported.

Figure 13. View of the nine-monitor display stand from the front and side.

Each of the monitors had a plastic bezel, or border, surrounding it. The plastic bezel was ¾ inch tall and ¾ inch wide. So, when the monitors were tiled together there was a 1 ½ inch border between monitors. The entire display was 36 ¾ inches tall by 44 ¼ inches wide. Each monitor had a diagonal physical size of 17.1 inches, 96 DPI, and a resolution of 1280×1024. The base of the stand was set on a workstation table (see Figure 13) approximately 30 inches from the ground. A standard keyboard and standard optical mouse were used to drive the machine.

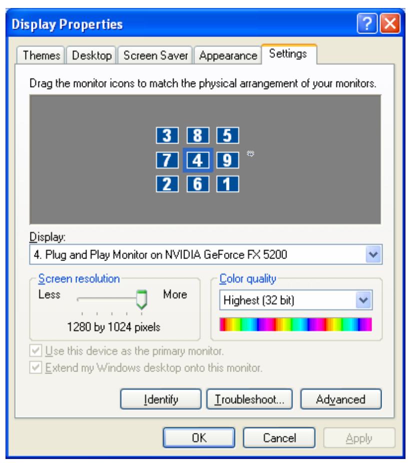


Figure 14. Screenshot of the Windows XP Display Properties dialog box. This dialog box allows for easy configuration of multiple monitors.

With plug and play technology we were able to quickly arrange the monitors in software using the standard Windows display properties dialog box (see Figure 14). Such software allows the operating system to create a virtually seamless desktop. Figure 15 shows an example of one image being shown on all nine monitors. The operating system does not make applications aware of the monitors, but rather gives applications the size of the virtual desktop.

Figure 15. Completed picture of the nine-monitor display with a single image being displayed.

4.2 Windows Software

In addition to using Windows for the first 3 experiments, ESRI ArcView software was used in the second experiment (see section Chapter 6). ArcView is a full-featured GIS software for visualizing, analyzing, creating, and managing data with a geographic component. Most data has a component that can be tied to a place: an address, postal code, global positioning system location, census block, city, region, country, or other location. ArcView allows users to visualize such data to help reveal patterns and trends [44].

ESRI, the company that creates ArcView explains that ArcView is used for a variety of purposes including the following:

- City and county governments manage local zoning, land use, and property tax assessments.
- Law enforcement teams track and analyze crime incidents.
- Real estate developers locate new commercial development sites.
- Fire and rescue services officials map fire spread, property damage, and resource allocation.
- Utility companies map services and customers.
- Military commanders analyze tactical plans.

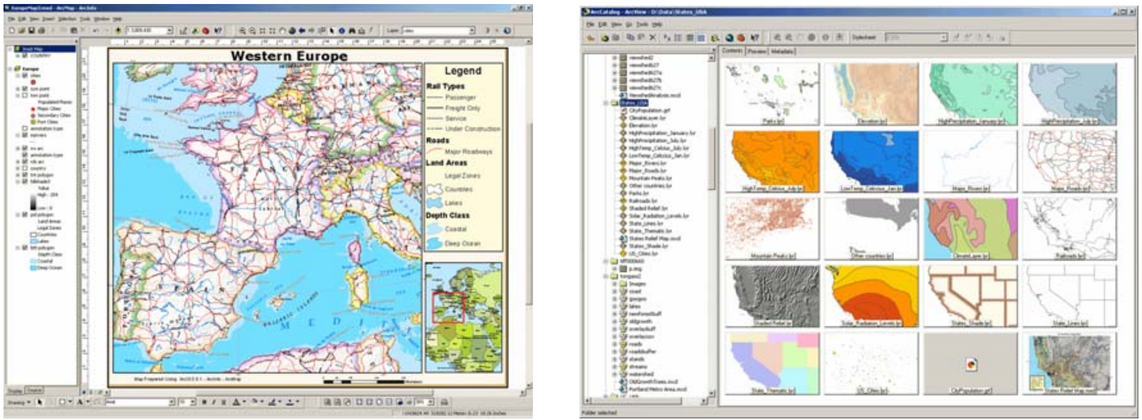


Figure 16. Example screenshots of Arcview from [44].

4.3 Linux Cluster – 24 Monitors

After the 3rd experiment we created a larger display. Instead of nine tiled monitors, we used twenty-four tiled monitors. Unfortunately, neither the Windows operating system nor the hardware associated with the computer we were using to power the nine-monitor display were able to handle the load of twenty-four monitors. As a result, we created a Linux cluster that could handle the performance demands of the larger display.

Figure 17 shows the back of the Linux display cluster. For reasons of affordability and maintenance we adopted a two-to-one model of one computer to every two monitors using dual-head graphics cards. We connected the cluster together using gigabit Ethernet with eleven standard machines and one high-end server.

Figure 17. Shot of the back of the display cluster showing computers driving the display.

In addition to enlarging the display we removed the plastic bezel to reduce the physical distance between monitors. By removing the plastic bezels we reduced the gap between monitors from 1 ½ inches to ¾ inch for adjoining monitors from side to side and to 1 inch for adjoining monitors from top to bottom. (Although the plastic bezel was a constant width on top and bottom and the sides the underlying metal had a different width and height of metal bezel.)

The nine-monitor stand used was a static flat stand. However, for the twenty-four monitor display we made each of the eight columns used for the display into atomic mobile stands. Each stand was independent for the express purpose of allowing reconfigurability and display curvature. Figure 18 shows a user with the twenty-four monitor display as it is curved around him.

Figure 18. Example of a user interacting with the curved display using the VICON system as an input device.

Unlike Windows which was plug and play, there were two important pieces of software that were used with the twenty-four monitor display to improve functionality: DMX and Chromium. These two pieces of software allowed us to achieve a virtual desktop for all twenty-four monitors.

4.4 DMX

DMX (Distributed Multihead X) is a proxy X server that provides multi-head support for multiple displays attached to different machines each running an X server. When Xinerama is used with DMX, such as we used with our experiments, the multiple displays on multiple machines are presented to the user as a single unified screen [36].

There are two ways to control DMX. The first is to use a console window and the second is to use the large virtual desktop as one would normally a virtual desktop without DMX: with a standard keyboard and mouse. However, in order to gain the maximum number of pixels from a large display one might control the display from an external source. One common way of doing this is using the control panel approach. This approach involves controlling the display from another machine. The main advantage to this is that every pixel on the large display can be used for viewing data without the need to waste space for interaction purposes. Historically this approach is most common.

Unfortunately, when using this approach one usually uses a display that is smaller than the display one is trying to control introducing less than a one-to-one mapping of pixels. For example, *Figure 19* shows a control panel that shows all of the windows that are present on a 2×3 tiled display (2560×3072); the monitor that the console window is on is only 1280×1024.

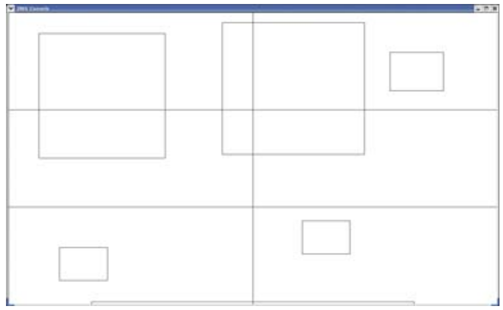


Figure 19. A screenshot of a DMX console window. DMX is a program that unifies different X servers. (X servers are the GUI environments for Unix-based operating systems.)

The second approach, and the approach used in our experiments, is to interact directly with the large virtual desktop. The user uses one keyboard and mouse to control the entire display.

This causes problems with interaction as the twenty-four monitor display is so physically large that if a user were on one end of the display when it is configured flat that it is difficult to see where the cursor is and be precise in pointing and clicking. As a result, we used a wireless 3D gyro mouse for the capstone experiment to enable users greater range of motion.

Technically speaking, the user uses a keyboard and mouse that is connected to a single machine. That machine in turn sends the appropriate keyboard and mouse events as needed to the other machines as appropriate. This feature allowed us to use a single input device to control all of the twenty-four monitor display at once.

4.5 Chromium

In conjunction with DMX we used chromium. Chromium is a system for interactive rendering on a cluster of workstations. It is an extensible architecture, so that parallel rendering algorithms can be implemented on clusters. Chromium is derived from the WireGL project [161] which had similar goals, but was more tightly controlled.

Chromium provides an OpenGL [101] abstraction which includes a parallel interface and a generalized stream processing layer. OpenGL applications must dynamically link to the OpenGL library in order to support a variety of graphics cards. Chromium exploits this dependency by using its own interception library to masquerade as the system's OpenGL library. An important side effect is that Chromium is transparent to a running application. One very important way in which Chromium differs from OpenGL is that Chromium supports parallelism [29].

Figure 20 shows an example of Chromium being used with Quake 3 with the twenty-four monitor display. By using Chromium we were able to run a variety of applications, such as Quake 3 in real-time. Such performance would not be possible without parallelization.

Figure 20. Quake 3 running at 10240x3072 resolution at 15-30 FPS. This is possible due to Chromium.

In addition to parallelizing OpenGL commands, Chromium has a feature that allows images to be shown in parallel. Called dist_texture, or distribute texture, it supports loading of texture images on different machines. The point is to avoid the cost of transmitting texture images over the network. This can be a bottleneck in performance when large number of texture images are sent over the network to many machines.

Technically, dist_texture overloads the glTexImage2D function in the OpenGL API. By adding two new values of GL_TRUE and GL_FALSE, Chromium is able to write or read texture images to or from the different machines in the display cluster. Specifically, when the parameter GL_TRUE is sent then a texture image is sent over the network and saved on the local machine. On the other hand, when GL_FALSE is sent then the texture image is loaded locally from the local machine.

The idea is that a program can use write-mode to distribute texture image data on a rendering cluster the first time the program is run. Then, the second and subsequent runs can use read-mode to quickly read the texture data from the local machines servers, instead of passing it all through the network.

The dist_texture option was used extensively in the capstone experiment to improve response time of the OpenGL program. We estimate that the response time of the program was improved approximately three times.

4.6 TerraBlaster

An open-source program called TerraBlaster, which was written at NCSA, was used for the last two experiments. TerraBlaster is an OpenGL program that downloads images from the USGS teraserver database on demand and stores them in a local cache. The USGS teraserver database is a 3.3 tera-byte online database of high resolution USGS aerial imagery for all of the United States.

We heavily modified the program for the purposes of the experiments. We added a number of different interaction techniques that enabled us to carry out our experiments.

Specifically, we modified the program to be mouse-based. Previously the program was driven entirely by a control panel. Different arrows would have to be clicked to pan or zoom. Our modifications allowed the user to pan and zoom similar to Adobe reader. All navigation can now be performed entirely without the control panel.

DMX allowed us to use one mouse to control TerraBlaster and Chromium, with the dist_texture option on, allowed us to use the program in real-time.

4.7 VICON System

For the capstone experiment we also used a VICON system. A VICON system has the ability to track physical movement of objects in a 3D space. We used the system to track the head movement of participants.

Technically, the VICON system is able to track small reflective beads using infrared light. The VICON system is a precise system that tracks objects' positions sixty times per second.

Figure 21 shows a person wearing the hat that was used for the capstone experiment. The hat had reflective beads placed on it so that the VICON system could track its movement. The red-lit cameras are part of the VICON system that tracks the beads' position. The VICON system can be used in real-time or the objects positions being tracked can be recorded. We recorded the position of participants' movement for later analysis.

Figure 21. Tracking by the VICON system.

We wrote a server-client program that allowed the VICON system to be controlled by the proctor of the experiments. This allowed the proctor to turn on or off recording of the participants' positions to coincide with the actual tasks. The program also created customized output for more specific analysis of the experiment.

Specifically, we were able to automate the virtual and physical recordings of the participants' behaviors. By connecting the virtual navigation recording data to coincide with the physical navigation data from the VICON system we were able to analyze the virtual and physical navigation data that occurred at the same time.

Chapter 5 Study 1 – Basic Perception and Navigation

The goal of this experiment was to understand how perception and navigation play a part in performance. We used different viewport sizes on a nine-monitor display to see how differently they affect performance (see Figure 22).

Naively, one might expect that more pixels are always better, particularly in data visualizations where the goal is to enable users to absorb large amounts of information quickly. However, it is not evident if increased resolution would be beneficial, or to what extent.

Figure 22. The nine-monitor tiled configuration. The total resolution is 3840x3072 (11,796,480 pixels).

The fundamental issues are summarized in Table 1. The critical tradeoff revolves around data access. Low-resolution display offers a smaller viewport into the data space. Hence, it provides less simultaneously visible data items or less data detail, and requires more virtual navigation of the viewport to access remaining hidden data or detail.

Table 1. A summary of tradeoffs related to view and navigation issues for low or high resolution.

	View	**Navigation**
Low Resolution	Fewer data items visible or data items have less detail.	Increased virtual navigation, less physical navigation.
High Resolution	More data items visible or data items have more detail.	Decreased virtual navigation, more physical navigation.

On the other hand, high-resolution displays offer a larger viewport. Hence, more data and detail is displayed at once. However, because the resolution and size is larger, perhaps exceeding human perceptual limitations, more physical navigation may be required. In general, based on a space-scale analysis [51], less virtual navigation is required to access all portions of the total data space.

What is the benefit of increased visible data of high-resolution displays? If there is a perceptual performance benefit, how much is it? What is the effect of the navigation tradeoffs associated with using such displays?

We presented this experiment at ACM SigCHI 2005 [9]. It introduced a number of questions that led to a number of other experiments. Possibly the most important part of this experiment are the results that show how the performance time for varying viewport sizes is dependent on the scale of the dataset.

5.1 Experiment Design

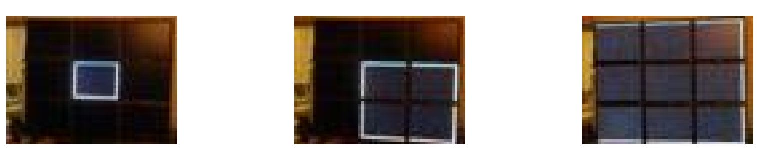
The goal of this experiment is to explore the fundamental tradeoffs between low- and high-resolution displays for basic low-level visualization and navigation tasks. We were especially interested to see how people's behavior differed for low-resolution and high-resolution displays. These issues are studied in the context of large 2D spatial data spaces, containing small finely detailed data objects. These data spaces are modeled after common visualization applications such as GIS, satellite, or astronomical data images. Participants must find various visual features within the large 2D space. The 2D virtual navigation used in this experiment is based on simple zoom+pan interaction.

This 3x3x2 design experiment has 3 independent variables:

- Viewport size (total number of pixels):
    a. One monitor: 1,310,720 pixels
    b. Four monitors: 5,242,880 pixels
    c. Nine monitors: 11,796,480 pixels.
- Target size (with respect to the total 2D data image size): Large, Medium, and Small targets.
- Task type: Find target, and Compare targets.

5.1.1 Displays

The three display resolution conditions were constructed from tiled LCD monitors (see Figure 23). Each LCD monitor has 17 inch diagonal with 1280x1024 resolution. Figure 22 shows the 3x3 nine-monitor configuration, the condition with the highest resolution. The four-monitor condition used a 2x2 tiled array. The one-monitor configuration is a single LCD.



A) One monitor *B) Four monitors* *C) Nine monitors*

Figure 23. Image showing the use of one monitor (1280x1024), four monitors (2560x2048), and all nine monitors (3840x3072).

All the images were designed to fit on the nine-monitor display. The software used showed the image without scaling it on nine monitors. To see the entire image at once on four monitors the image had to scale by a factor of 0.44. On one monitor the image had to scale by 0.11.

5.1.2 Data and Targets

For purposes of control, we developed data images containing controlled visual stimuli that were fabricated solely for the purpose of this study. We did not intend to study a particular visualization technique or representation, but to study basic perception and navigation. Data images were high-resolution (3840x3072), containing small number of red dot stimuli in a sea of thousands of grey dots. The red stimuli were the targets of the participant tasks.

Since the granularity or scale of the targets within the 2D data space is likely to affect user tasks at various display resolutions, we varied target size to measure the effect.

Our motivation for this study is based on real data visualization problems of not having sufficient screen space for one's data. In order to analyze our research questions effectively it was necessary to create a controlled setup. As a result we created data visualizations that were fabricated solely for the purpose of this study.

For the data that we created there were small dot images that had 240,000 gray dots, medium dot images that had 120,000, and large dot images that had 60,000, as shown in Table 2. Both the gray dots and the red dot varied according to the table at the different scales. The gray dots acted as distracters so that the participant would not be able to immediately spot the targets.

Table 2. Experiment specification for the comparison task.

Experiment	Number of gray dots	Gray dot size (in pixels)	Red dot size (in pixels)
Small target	240,000	4	6
Medium target	120,000	8	12
Large target	60,000	16	24

For each task the participant in the study was given an image that had red targets and many gray dots on a black background. Both the red dot and gray dot had the same luminance of 120. The reason for the black background was to help the user find the red dot faster. Also, the red dot was slightly larger than the gray dots to help the participant identify it faster.

5.1.3 Tasks

Two basic visualization tasks were examined: finding a single target, and identifying paired targets in a high-resolution image.

5.1.3.1 Find Task

The first task, finding an anomaly, consisted of finding a red dot out of thousands of gray ones (see Figure 24). Participants were timed on how long it took them to identify the red dot.

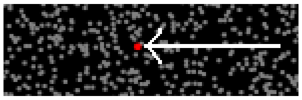
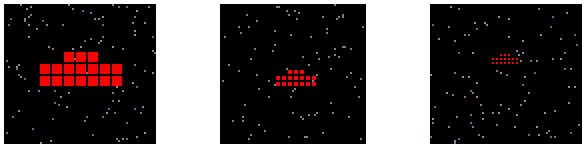


Figure 24. Drawn arrow to show example of a red dot. This image is cut out of the larger image that has a resolution of 3840x3072. White arrow was not part of the original image.

5.1.3.2 Comparison Task

The second task, a comparison task, consisted of finding red targets in an image and identifying pairs. This task was more sophisticated than the first task in that the participants had to first find the red targets then compare all of the targets with each other to identify the pairs.

The participants were given an image with 14 targets. There were triangle, square, horizontal rectangle, vertical rectangle, diamond, top hat (see Figure 25), and upside-down top hat pairs. Each target was made of dots. For example, a triangle was made up of three dots and the top hot was made up of two rows of eight dots topped with a row of three dots (see Figure 25 to see the top hat). For each image there were 100,000 gray pixel distracters in the background.



A) Large B) Medium C) Small

Figure 25. Example target that was used in the comparison task. The following figures show the same target at the various size dots hat make up a target: A) Large dot size (16 pixels per dot) B) Medium dot size (8 pixels per dot) C) Small dot size (4 pixels per dot).

5.1.4 Navigation

To accomplish the tasks, participants used the standard Microsoft image display software, called Picture and Fax Viewer, which supports simple zoom and pan navigation. The nine-monitor configuration is large enough that zoom+pan is not needed to view the full image space. In the other conditions, zoom+pan were used out of necessity. Hence, this tests virtual navigation versus physical navigation. Participants were still able to zoom in or out and pan on the nine-monitor configuration (although few participants actually did).

The dependent variable was performance time for each task. We measured how long it took to complete each task.

5.1.5 Design

The experimental design was between-subject for the different dot sizes and within-subject for the different resolutions. In other words, the experiment was setup to have each participant on all three monitor configurations, but participate in only one dot size.

Our independent variables were target size and resolution. We wished to see how the performance time of our tasks (dependent variable) changed as the target size and screen size were changed.

For each experiment, each subject participated in three find tasks and two comparison tasks on one monitor, four monitors, and nine monitors for one dataset. All the combinations of monitor size were tested equally.

There were three different datasets that differed in size. Each dataset was performed by 12 different participants. In summary, there were 36 tests run with each participant performing three find tasks and two comparison tasks for each monitor configuration (one, four, and nine) for a total of 324 find tasks (three find tasks X three different monitor configurations X three data sets) and 216 comparison tasks.

5.1.6 Participants

All 36 participants (13 female, 23male) were volunteers that were college students from a variety of majors. The ages of the participants ranged from 20 years old to 29 years old. All participants performed both types of tasks on all monitor configurations, but on only one particular target size. All participants were given a training session prior to actual testing.

5.2 Quantitative Results

Using traditional statistical methods, such as ANOVA and post-hoc contrasts such as the Tukey procedure, with $\alpha = 0.05$ we found significance only for the small targets in the find task. In other words, we could not statistically say that any monitor configuration gave better performance time than any other when using the medium or large targets (see Figure 26). However, using the small targets we found statistical significance between the one monitor and the nine monitor configurations. In other words, there appears to be a considerable trend indicating that the larger configurations produce a better performance than the smaller configurations when dealing with finer detail data.

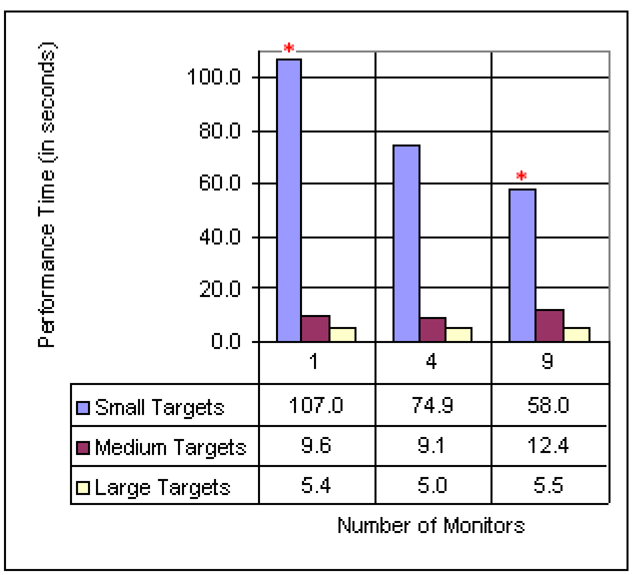


Figure 26. Performance data for the find task. Statistical significance is indicated with a red asterisk.

For the small targets in the compare task, we found that there was statistical significance between the four and nine monitor configurations (see Figure 27). With the medium target size, the four and nine monitor configurations were better than the one monitor configuration. For the large target size, there was no statistical difference between any of the monitor configurations. In general, the smaller the target size for the compare task the larger the display needed to be to increase the performance time.

Our data suggests that nine monitors did not ever slow down participants, but rather drastically improved performance time with smaller targets. With the case of the large targets, the performance time of the nine monitor configuration was approximately the same as the one monitor configuration. On the other extreme, participant's performance time on the nine monitor configuration was less than half of the performance on the one monitor configuration. It also shows that the four monitor was never worse and was sometimes better than the one monitor configuration.

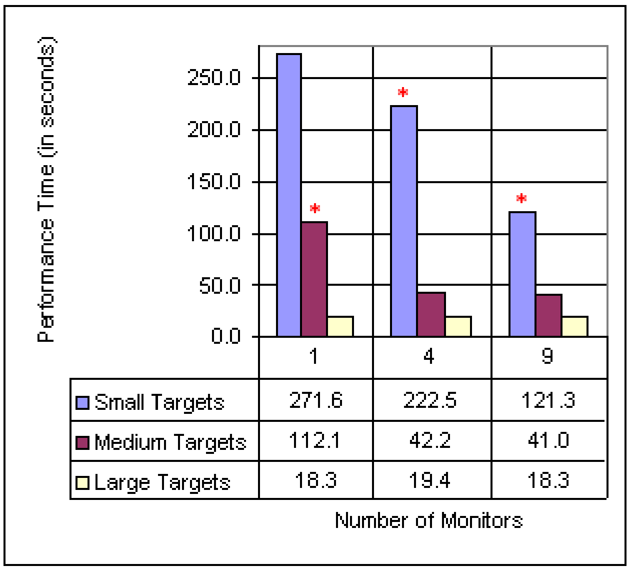


Figure 27. Performance for the comparison task. Statistical significance is indicated with a red asterisk.

5.3 Observations

This section highlights the most common observations that were observed by several or all of the participants.

5.3.1 High-Resolution

5.3.1.1 Larger Resolution and Physical Navigation Decreases Repetition and Increases Confidence

When participants used either the one or four monitor configuration, they would sometimes report the same pair of targets more than once. Approximately one-third of the participants accidentally reported a result more than once with the one monitor configuration. Approximately one-sixth of the participants did the same with the four monitor configuration. Reporting the same target pairs twice never occurred on the nine monitor configuration.

Our hypothesis is that because the image never moved with the nine monitor configuration the participants were able to remember the spatial position of targets better. If zooming or panning were used extensively then targets would "move" – the view point of the participant changed and the targets would change positions accordingly. The absence of repetitive reporting of the same pairs for the nine monitor configurations points to a lighter cognitive load.

Using the one or four monitor configurations participants would occasionally be unsure if they had found the second target to a pair or had simply found the same target twice. On the other hand, participants were able to be fully confident that they had not found the same shape twice with the nine monitor configuration, as they could literally put one finger on one target and another finger on the other target, clearly showing that the two targets were a pair.

5.3.1.2 Physical Navigation Preferred

Although zooming was more popular than panning, participants preferred not to interact with the mouse at all. Several participants explained that they would rather squint at indistinct targets than actually zoom in. The participants wanted to evaluate the data as much as possible before touching the mouse. Participants tended to zoom and pan only when targets were too indistinct to see.

One possibility to explain this observation is that people do not like to lose context. By panning and zooming participants lose context and get frustrated. Some participants exhibited a great deal of frustration in their body language and speech as they explained that they continuously felt lost and confused with the one and four monitor configurations. This was especially prevalent when using the small targets. At times the proctor had to calm the participant down before he would continue. The most frustrated individuals used exclusively pan and did not consider the idea of zooming. Another possible explanation why participants did not like to interact with the mouse is that they simply do not like to expend effort on interacting as they would rather move their bodies as in the real world.

5.3.1.3 Overview, Even with Physical Navigation

Participants preferred to be in a zoomed out mode. With the nine monitor configuration, participants preferred to step back from the monitors to get an overview picture first then step forward for more detail.

When dealing with the nine monitor configuration, participants preferred to look at one monitor at a time when stepping forward for detail. This strategy is similar to the strategy used with virtual navigation when panning. However, instead of getting lost in the display space, the bezels between the monitors acted as natural dividers to help orient the participants.

Also, participants tended to walk, crouch, and have more overall physical movement. Although this aerobic computing was effective, people would also sit down and examine large areas of the screen from an adjustable chair.

5.3.2 Low Resolution

5.3.2.1 Zooming is preferred to panning

Our observations showed that our participants really did not like to pan (use scroll bars). In fact, over half of the participants instead of ever panning with a scroll bar would "pan" by zooming out to a certain point and zooming in at areas of interest. If panning was used, they only panned to nudge a target into the screen.

We also confirm Furnas and Bederson's analytical analysis that zooming is faster than panning [51]. Through our study we show that people prefer to zoom over panning. Those participants that preferred zooming to panning performed better than those that simply panned.

5.3.2.2 Problems with panning – increase in disorientation

Participants that did pan tended to get worse times than those that did not as they would get lost in the image space. Several participants complained that they got lost in the large space when panning as they only had the scroll bars as context. Participants that would only zoom did not lose context as often as they would zoom out as much as possible, pick a spot of interest and zoom in. Once that spot of interest was visited they would zoom out again.

Participants that panned would become systematic by the end of the experiment in the way that they looked for the target. All but one participant that panned would scroll to the top-left of the image. They would then start scrolling little by little to the right until they reached the far right of the image. Then they would quickly return the scroll bar all the way to the left, and then scroll down a little. They would then repeat the pattern of slowly moving to the right. The only participant that did pan but did not follow the above algorithm reversed it; the participant went from right to left instead of left to right.

If this systematic approach did not work then participants would usually be convinced that the proctor was trying to trick them and that the desired target was not actually there. Once the proctor reaffirmed that all images had the appropriate target most participants would get agitated and either start the systematic approach again or randomly look for the target. There were many instances after such tasks that participants had to be shown that it was in fact there before continuing to the next task.

5.3.2.3 Panning or Zooming – Not Both

Our observations showed that participants did not extensively use pan and zoom together. Participants that did pan would zoom into the image to the point that they could see enough detail to their satisfaction and then would only pan from there on. People that preferred to zoom tended to seldom use pan as mentioned above. We did not observe any participants that used zoom and pan equally.

5.3.3 Focus Areas

When participants used the nine monitors they would often focus on the bottom two rows. For example, for an average-sized participant using the nine monitors and the target they were looking for was on one of the top three monitors it took them on average twice as long to find it than if it were on the bottom six monitors.

Tasks where the target was close to a bezel (within 1.5 inches [3.8 cm]) took 3 times more time than if the dot were farther away. This phenomenon occurred only with the nine and four monitor tasks as the one monitor tasks did not span monitors.

Another interesting observation is that people tended to not find objects in the center of the image whether it was for nine, four, or one monitors. For the first few tasks participants initially looked in the middle of the image, but after that they would look more around the edges than the center.

If a target pair near to each other then they were always identified. However, if the target pairs were far apart from each other then the farther apart they were the less likely they were to be identified with each other. With one monitor this meant that because of the timeout target pairs that were physically distant were seldom identified.

5.4 Conclusions

High-resolution displays can be a benefit in that they significantly improve performance time for basic visualization tasks in finely detailed data. We found that the high-resolution displays help people find and compare targets faster (up to twice as fast), feel less frustration, and have more of a sense of confidence about their responses than on a single monitor.

It appears that performance time is correlated more to the scale, or granularity, of the dataset and tasks than with viewport size alone. Increasing the viewport size only helped decrease performance times with deeper scaled, finer grained, data.

We found that there is more physical navigation for high-resolution displays and more virtual navigation in low-resolution displays. Also, from our observations there appears to be a greater amount of frustration when dealing with pan+zoom as opposed to physical navigation. When participants used pan+zoom with the one and four monitors they would often become disoriented and agitated. The participants were more prone to believe that a target they were looking for did not exist when not immediately found.

5.5 Next Step

This experiment led us to question whether our results were only valid for abstract spatial targets or if the results would continue for other tasks and datasets. Specifically, we wanted to know if our results were valid for more general usage, such as with maps.

Chapter 6 Study 2 – Navigating Large Maps

The goal of this experiment was to understand how viewport size affects large maps. Specifically, do larger viewport sizes always help improve performance time? Will the results from the last experiment differ from this one?

Using maps is a universal task with which almost all of society deals. Whether one is planning a road trip, or going to the grocery store, maps are extensively used. However, not all maps are the same. Maps greatly vary in the amount of detail they provide. As a result, it is logical that a small display might not be suited for a detailed map and that a large display might not be suited for a sparsely detailed map.

This experiment is the first half of a paper that we presented at Iasted-HCI '05 [10]. The first experiment (Study 1) introduced the notion that larger displays help with performance with large datasets and tasks. We performed this second experiment with the intention of understanding how the results of the previous experiment might be different when applied to actual maps.

6.1 Experimental Design

Using a detailed raster map (a map made of pixels as opposed to a vector map that is redraw using vertices) of Rhode Island, we conducted an experiment that compared different map tasks with three different display sizes; the same conditions as were used in Study 1 in Chapter 5 (see Figure 25). With the help of geographers we gave participants common map tasks which ranged from searching for a particular landmark to tracing a route from one location to another. The map used in the experiment would have covered the equivalent of 22 monitors if all detail were to be shown at once.

Using a between-subject design, all participants used the same map of Providence, Rhode Island. Performance time and accuracy were recorded as the dependent variables. Each participant was randomly assigned to a monitor configuration. Each participant was given a brief five to ten minute tutorial on how the software worked using a practice map prior to the actual experiment.

For this experiment, we used pan and zoom as our interactive technique. The software that participants used to navigate the map was ArcView: a full-featured GIS software program for visualizing geographical data by Environmental Systems Research Institute (ESRI). Participants were filtered to ensure they had no prior experience with ArcView.

6.1.1 Tasks

Common usages of maps include route tracing to more complex tasks such as deciding where a building should be erected. As a result, our experiment included six different types of tasks: Three search tasks; two route tracing tasks; two counting tasks; five comparison tasks (e.g. Which destination is closest); three intermediate tasks (e.g. Find the deepest water in Providence River); four advanced understanding task (e.g. Why is this area not developed?)

6.1.2 Participants

All volunteers for the two experiments were screened prior to participation. All participants were required to have normal to corrected-normal vision, no color blindness, no familiarity with traveling/navigating through the state of Rhode Island (all maps used were from the state of Rhode Island), and no prior experience with large displays.

All participants were undergraduate students between the ages of 18 and 24. Twenty-four people participated. They were all male computer science undergraduate students who received extra credit for their participation.

6.2 Quantitative Results

Using standard ANOVA techniques, we found that the search and route tracings tasks were more than twice as fast on the nine monitor display as on the one monitor display. In other words, participants were able to search for objects in previously unknown locations and trace a route, or path, from one location to another, more than twice as fast with the largest display size than the smallest display size.

In particular, we found the search task correlated to display size ($p < 0.01$) with differences between the one and four monitor configuration and between the one and nine monitor configurations. Figure 28 shows that the search task was performed more than twice as fast on the nine monitor configuration than on the one monitor configuration.

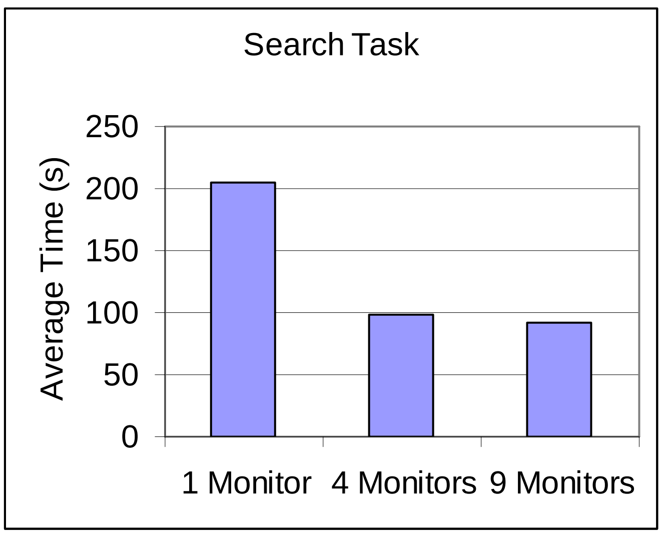


Figure 28. Average time in seconds for a participant to find a particular object or location on the map at different monitor configuration sizes.

The route tracing tasks also showed statistical significant ($p < 0.01$) when correlated to display size. Participants were instructed to trace a route from a source location to a destination location. Participants were able to accomplish this task on the nine monitor configuration more than twice as fast than on the one monitor configuration. Figure 29 shows the same trends as Figure 28; participants were able to trace routes more than twice as fast on the nine monitor configuration compared to the one monitor configuration.

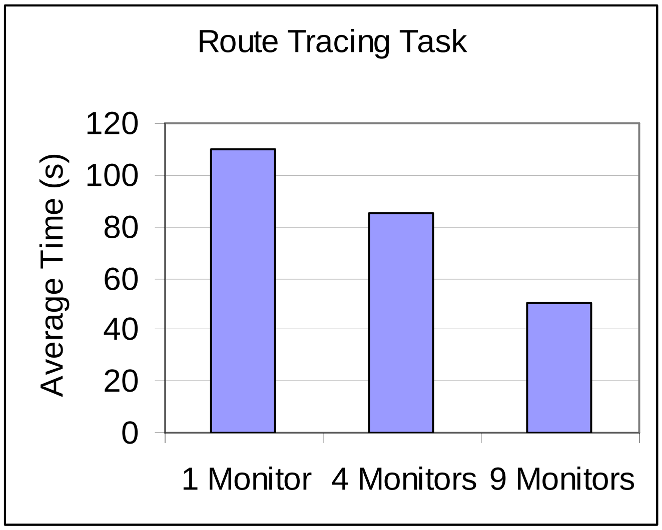


Figure 29. Average time in seconds for a participant to trace a route on the map at different monitor configuration sizes.

One reason for the increase in performance times could be the fact that participants on the larger monitor configurations navigated less with the map. In effect, as participants could see more of the map at a time, less navigation was required and consequently more time could be spent on the task at hand.

The other tasks did not have statistically significant results. In general, the other tasks were more advanced geography tasks that most of the participants had never performed before. Current work is being performed to understand how those tasks are affected by viewport size using expert geographers and cartographers.

6.3 Qualitative Results

Although bezels are generally considered a distraction [83], we observed that participants used bezels to their advantage during most of the tasks. When using the larger displays participants used the bezels to segregate the map into portions. For example, by dividing the map into parts they were able to better keep track of which part of the map they had previously searched to their advantage.

This strategy is similar to a divide-and-conquer strategy. Participants would thoroughly use each segment of the map that corresponded to a particular monitor before proceeding to another monitor. Using this approach participants were able to better remember what areas of the map they had and had not used using external memory.

We also observed that on the smaller displays people were more algorithmic in their approach to finding objects. On the largest display participants rarely did so. For most tasks, especially the search tasks, participants on the nine monitor configuration would use more intelligent heuristics, or guesses, to finding an object. For example, instead of searching the entire map for a university, as did most participants on the one and four monitor configurations, the participants on the nine monitor configuration would search logical areas, such as dense city areas or other areas that a university would logically be located.

This gives indication of increased insight and awareness into the overall map [126]. By being able to see both more overview and more detail at the same time participants were able to think more about where objects most likely would be, not simply look at all possible positions. The implications of this observation are that by being able to see both more overview and more detail one does not get information overload, but actually is able to make better, more informed decisions.

We also observed that participants did not in general like to zoom in. If possible, participants would use the bounding box zoom rectangle to clip out all unnecessary parts of the map for the task. Then participants would often squint at the overview to try to gain as much detail as possible without having to actually zoom in any further and lose context of the entire overview.

6.4 Conclusion

We found that performance improvements were once again seen using larger viewports sizes. However, after both Study 1 and Study 2, it appears that viewport size helps performance time based not only on the scale of the dataset but the task as well. For example, Figure 28 shows the start of diminishing returns for while Figure 29 shows constant improvement. As both tasks used the same map, we conclude that the reason for the differences in performance curves is due to the scale of the tasks.

Another important find from this experiment is that participants were able to use better strategies to accomplish their tasks. Seeing more overview and details helped participants use better strategies for the particular tasks at hand.

6.5 Next Step

So far we found that performance time with static maps and static spatial images can be improved. However, a pressing question was whether the results could be extrapolated for dynamic maps. Although the use of static maps is common, another common scenario is the use of dynamic maps from traffic control analysis to battlefield command.

Chapter 7 Study3 - Dynamic Geospatial Environments

The goal of this experiment was to understand how varying degrees of viewport size affect performance for dynamic environments – as opposed to static ones that had previously been tested. In order to best test a dynamic environment we used a strategy game.

We chose to use a real-time strategy game because of the similarity between such games and real-life scenarios of control room situations and it was a natural fit for the increased number of pixels.

This section presents the results from a controlled experiment, usability evaluations, and user feedback. In the experiment participants played Wargus, a real-time strategy game based on WarCraft® II (see Figure 30). The experiment examined gamers in a series of competitive game tournaments with human participants and different display sizes and resolutions. This study revealed the advantages of higher resolutions as well as a number of human-computer interaction factors, such as user interface and notification system issues. Specifically, our research questions are:

- Do larger displays improve gamer performance? If so, how much improvement is gained by incremental increases in display size?
- What user interface, notification, and other usability issues arise on larger display configurations? How can these be solved?

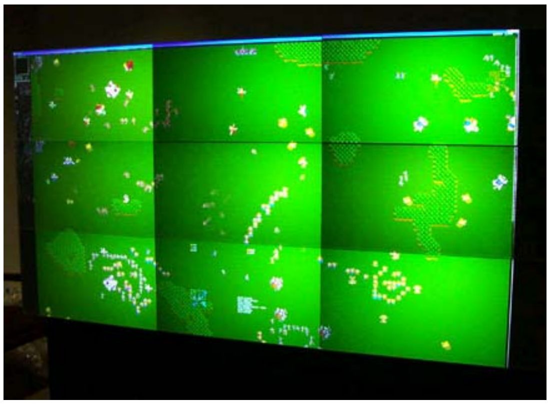


Figure 30. Wargus, a real-time strategy game, being played on nine tiled screens at a resolution of 3840x2160.

This section shows that large, high-resolution displays greatly enhance the gaming experience. The majority of gamers preferred the dramatic increase in resolution and detail in comparison to the lower resolution version of the same games. We found that there are measurable benefits in that users score higher, require less virtual navigation, and have a greater awareness of the environment.

This experiment is presented in the first half of a paper in the *Interacting with Computers* journal [123]. The second half of the paper includes further work on awareness and notification systems for gaming with large displays.

7.1 Experiment Design

Our independent and dependent variables are explained in Table 3 and Table 4.

Table 3. Lists the Independent variables for the study.

Display Size	Map Size
• 1 monitor (640x480)	• Small (2048x2048)
• 4 monitor (1600x1200)	• Medium (3072x3072)
• 9 monitor (2400x1800)	• Large (4096x4096)

Table 4. Lists the Dependent variables for the study.

• Game score	• Wins and losses
• Time spent panning the map	• Usage of the minimap

Using a tournament style approach, we held 10 competitions. There were three participants in each tournament (total of 30 participants) that played each other in a free-for-all style game three times. Each participant would play on each of the three different display sizes: one monitor, four monitor, and nine monitor tiled configuration. Participants were randomly assigned an initial display size and were given time to re-familiarize themselves with the game. Each experiment also contained a small, medium, and large map which was assigned randomly as well. We performed a full factorial design in which all display-size orderings were completed five times. In other words, each participant played at each display once, so after six participants, we completed a full factorial of display orderings. Since each participant used three different display sizes, participants were given time to familiarize themselves with their configuration before every game. Since we held 10 tournaments with three games per tournament, a total of 30 games were played.

Before a tournament began, participants were asked to fill out a simple questionnaire asking their age, gender, computer proficiency, and average number of hours they play video games a week. After each game, participants were asked to estimate approximately what percent of their time they thought they spent simply navigating the battlefield map. After all three games were completed in the tournament participants were asked which display size they preferred, and if the larger configurations helped and how.

7.1.1 Participants

For the experiment there were 30 participants each of whom had played at least 100 hours in WarCraft II® or a similar real-time strategy game prior to participation. Thus they were considered experts. All participants were between the ages of 18 and 23 with the average age of 20. There were 35 male participants and one female participant. All participants were undergraduate students from a variety of majors. The average time playing games per week is 9 hours ranging from 5 to 20+ average hours of game play a week on various video games.

7.1.2 Game Specifics

We used Wargus, an open-source project based on the WarCraft II® data and runs on the open-source game engine called Stratagus. Warcraft II® is a popular real-time strategy battlefield simulation game developed by Blizzard Entertainment.

Since Wargus is a strategy game based on gathering resources, building up forces, and attacking and destroying enemy forces, and users must interact with and manipulate their units in various ways. For instance, users are able to select their army by clicking on individual units or using a selection box to select multiple units. Each type of unit has different attributes and is controlled by control buttons on the left side of the screen or with hot keys. Status information and notifications are located at the top and bottom of the display. Wargus uses the overview+detail navigation technique (see Figure 31). In the overview (or 'minimap'), users can move the outlined rectangle that represents the position of the viewport by dragging it or by clicking on any area of the overview. Also, panning can be accomplished by using the arrow keys or mouse.

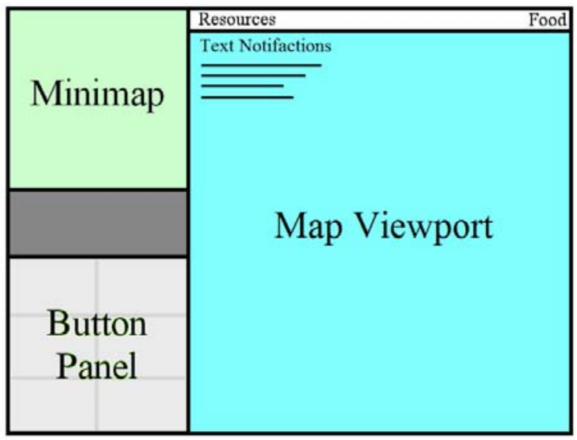


Figure 31. A diagram showing the locations of the minimap, user interface, and viewport.

We altered the source code of the game to track the dependent variables (e.g. game score, wins and losses, time spent panning the map, and usage of the overview window). We also made some changes to the game to isolate the visual components. As such, some features of the game such as sound notifications and fog of war were removed.

7.1.3 Hardware

For the experiment we used three computers with one, four and nine tiled monitors respectively as can be seen in Figure 32.

Figure 32. One monitor configuration (640x480), four monitor configuration (1600x1200), and nine monitor configuration (2400x1800).

The single monitor was set to have a resolution of 640x480 which is the default configuration for Wargus. The four monitor computer had a resolution of 1600x1200 and the nine monitor computer had a resolution of 2400x1800. Figure 33 compares the relative size difference between the one and nine monitor configurations. The one monitor configuration was kept at a low resolution for the purpose of seeing how a large resolution of the same game affects the user performance, navigation and interface design of the original, unaltered game. 2400x1800 was the highest resolution we could obtain at the time while keeping the game at real-time speeds on the nine monitor configuration.

Figure 33. Shows approximately the difference in size of the one monitor configuration (640x480) to the nine monitor configuration (2400x1800).

7.2 Quantitative Results

This section explains the major results from our study. First, how performance (score and wins) is affected by screen resolution, second, how navigation is effected by screen resolution, and lastly, how navigation effects performance. All statistical analyses were performed in SAS's JMP using standard ANOVA and Chi Squared techniques.

7.2.1 Score and Resolution Size

Participants using the large screen configurations scored higher than the participants using the smaller configurations with a statistical significance of $p < 0.01$. The average score on the one monitor was 2207, approximately 20% less than the four and nine monitor configurations. The score for the four and nine monitor configurations were approximately equal, 2659 and 2790 respectively. There were not any interaction effects between screen size and map size ($p = 0.76$).

7.2.2 Wins and Resolution Size

In addition to scoring higher, the participants also won more frequently on the larger, higher resolution displays. As can be seen in Figure 34, five of the 30 games (16.7%) played on the single monitor setup resulted in a win, 12 of the 30 games (40.0%) played on the 4 monitor setup resulted in wins and 13 out of the 30 games (43.3%) played on the 9 monitor setup resulted in wins. Performing a Chi Squared analysis, shows statistical significance of p = 0.032.

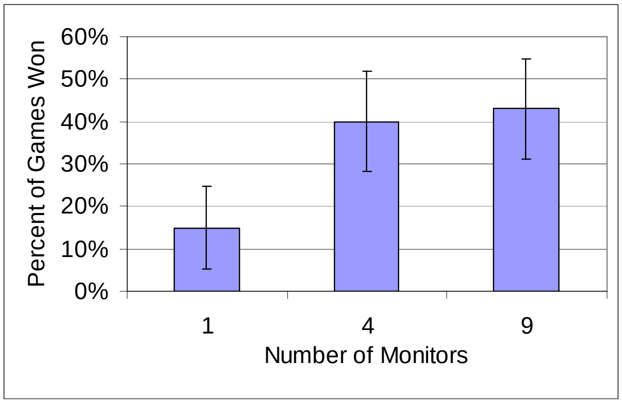


Figure 34. The percentage of games that were won on the one, four and nine monitor configurations. Larger sized screens won 2.5 times more often than the small screen.

7.2.3 Navigation Results

As explained earlier, we modified the open-source Stratagus graphics engine to track user input. Performing a two-way ANOVA of percent navigation revealed a main effect for display size (p< 0.01), a main effect for map size (p = 0.02), and no interaction effect between map size and screen size (p = 0.36).

Among our findings we found that the amount of time spent navigating varied on the different display sizes. Specifically, the smaller the monitor configuration was, the more time the participant spent navigating. We observed participants navigating in the following way: On nine monitors users navigated an average 5% of the game time, on four monitors users navigated an average 10% of the game time, and on one monitor users navigated an average 24% of the game time.

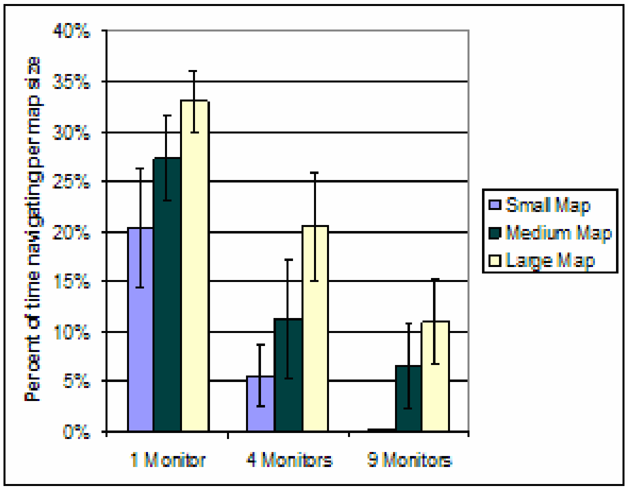


Figure 35. Percentage of the time participants spent panning the map related to the size of the map and screen size. Single-monitor participants navigated five times more than nine-monitor participants.

When comparing map size and screen size (see Figure 35), the amount of navigation varied across map sizes as well as display sizes. For example, on average there was little or no navigation on the nine monitors with the small map since the map was only slightly larger than the nine monitor display. However, as the map size increased the amount of navigation also increased.

7.2.4 Navigation Time and Performance

According to our results, time spent navigating affected score with a statistical significance of $p = 0.017$. Specifically, the less a participant navigated, the higher their score. Navigation also affected the frequency in which users won with a statistical significance of $p = 0.06$. As shown in Figure 36, if the percentage of time that a participant navigated the map is presented in intervals, it can clearly been seen that the less a participant navigated, the more frequently they won. These results show that we can decrease navigation by increasing screen size, and therefore increase user performance and allow the user to focus on game-play.

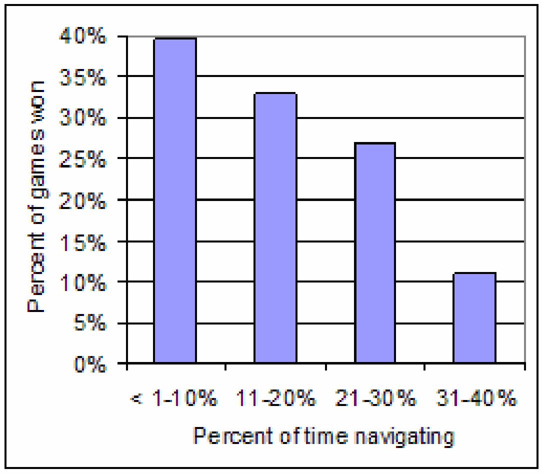


Figure 36. This graph shows how the time navigating affected the percent of games won.

7.2.5 Overview Interaction

By modifying the game engine, we were also able to track the interaction of the minimap, such as moving the viewport with the overview or issuing commands to units by right-clicking on the overview. With a statistical significance of $p < 0.001$ we found that the amount of times a participant would use the overview with the one monitor was greater than the four monitors which was greater than the nine monitors. As seen in Figure 37, participants used the overview less as the viewport size increased.

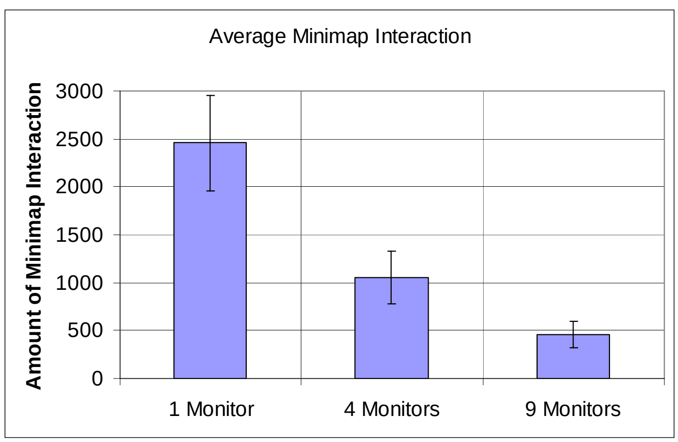


Figure 37. The average number of times mouse interaction was detected in the overview per game.

Using nine monitors, a much larger area of the map can be seen by the user at once (see Figure 38). By being able to see more context directly in the viewport, it was not necessary to navigate with the overview as much. Furthermore, since the minimap was located on the edge of the display, it required the large-screen users to move the cursor a much greater distance compared to the single monitor user.

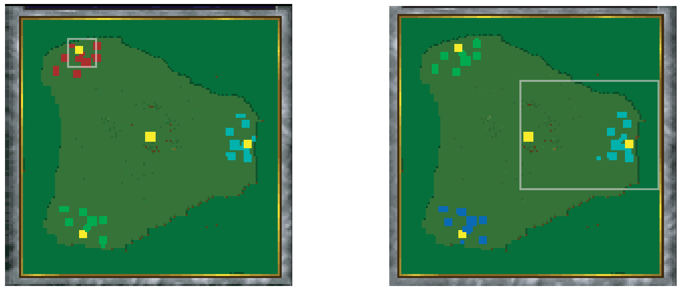


Figure 38. a) One monitor overview b) Nine monitor overview. The outlined rectangles in the overview shows how much of the map the user can see. The one monitor configuration sees only 5% of what the nine monitor configuration sees.

7.3 Notification Systems and Interface Design Issues

Seventy percent of the participants agreed that the notification systems and controls in the game were harder to use on the nine monitor configuration and had a negative impact on their performance. In the game there are several types of notification systems and controls. Figure 31 shows that there are several buttons as well as a minimap on the leftmost portion of the screen. On the top panel are several statistics that are important in the game that report total resources and units. The bottom panel shows how much a potential unit costs if the mouse is hovered over the button that creates said unit. In addition, important messages are printed to the top left of the viewport of the map.

All of these controls and notification systems are easy to use when they are close together. However, when using the nine monitor configuration it was difficult for participants to move their cursor over to the control panel. Following Fitts' law, it is more difficult to move the cursor to a target three screens away than it is to move a cursor to a target closer than the width of a single screen. Thus, by increasing the distance to the control buttons and the overview, it took participants much longer to accomplish basic game tasks on the nine monitor display.

As mentioned above, the notification systems were positioned at the top of the whole display. Since the notifications were positioned above the participant's line of sight on the nine monitor configuration, they claimed they didn't notice many, if any, of the alerts in the game. Since participants were not aware of vital events such as needing more resources, we speculate that the poor positioning of the interface had an adverse effect on the lower than expected user satisfaction of the largest configuration.

7.3.1 Bezels

Although bezels were only ¾ of an inch (1.9 centimeters) between tiled monitors, several participants felt that the bezels were distracting The was especially true on the four monitor configuration where the intersection of bezels in the middle of the display was a distraction (see Figure 39).

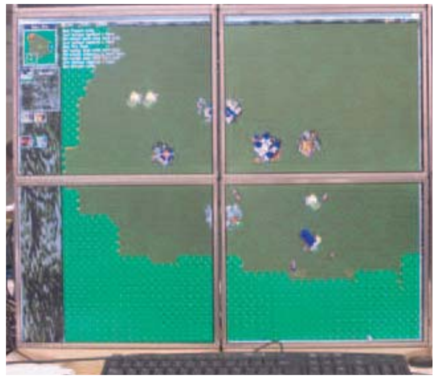


Figure 39. This image shows how participants view the four monitor configuration and see bezels in the middle of the display.

Another problem with the bezels is that the spatial distortion caused participants to misinterpret the size of their armies and bases. Looking at Figure 39, it appears that buildings that are on the monitor boundary are wider than they actually are. Similarly when a group of units crossed monitor boundaries it appeared to many participants that there were more units than that actually existed. This affect on users did not effect their performance as was found in Tan and Czerwinski [140]. However, Tan and Czerwinski did not identify the distraction reported by our participants. We speculate that the dynamic changes in the geospatial location of the data was the main cause for this reaction from participants.

7.4 Qualitative Results

We asked participants to respond to two questions: Which screen size did you prefer the most and why? Did the larger configurations help you in any way? How? They responded to the first question in the following ways:

Sixteen percent of the participants preferred the small screen size over the larger screens. They stated that they were more familiar with the one monitor configuration and disliked the bezels in the multi-monitor configurations.

Sixty-three percent of the participants preferred the four screens. The different reasons follow: Much more of the battlefield could be seen than in the one monitor configuration. They felt that the nine monitor configuration was too unfamiliar, and introduced problems in scalability of the original game's user interface.

Twenty percent of the participants preferred the nine screens. Their reasons were that less navigation was required, it was easier to interact with their units, and they had a greater awareness of the map.

In response to the question of whether the larger configurations helped and why, the vast majority agreed (90%) that it helped. They claimed an increased awareness of the entire battlefield, easier planning of strategies, and easier to interact with their units.

7.4.1 Base View

Construction and configuration of one's base can be important as all units are created at one's home base. With the one monitor configuration it was repeatedly observed that all buildings were built close to each other as all of one's base could not be seen at once and participants tried to minimize the amount of navigation spent just trying to view and manage one's base.

However, observing the participants on the four or nine monitor configuration, one could see that their base generally sprawled compared to the one monitor configuration as all of one's base could be seen at once on either the four or nine monitor configuration.

Participants on the one monitor configuration would often frantically navigate their base. They would appear to be constantly looking for threats in and around their base while at the same time maintaining their base.

On the four and nine monitor configurations participants would place their base in the middle of screen. As they could see their entire base there was not a need to be constantly navigating through their base as participants would be able to look for threats and maintain their base without scrolling. As a result of seeing more they would be able to look for threats in a wider area than simply in around their base.

7.4.2 More Global Understanding

As mentioned previously, users of the four and nine monitor configurations were able to look for threats further than just beyond their base. As a result they were able to respond to threats much faster than on the one monitor. For example, participants on the one monitor configuration would often respond to a threat after one or more of their buildings had been damaged or destroyed.

However, with the four and nine monitor configurations, participants would often respond to threats before the threat even attacked. There were suicide bombers in the game that could cause a great deal of damage, but were easily destroyed themselves. On the one monitor configuration participants would often either not see the suicide bomber but would simply notice later that a building or group of their units had been damaged or destroyed, or would notice the suicide bomber but not be able to react quickly enough. With the four and nine monitor configurations most suicide bombers were noticed and adequate retaliation could be used before the suicide bomber damaged anything.

In general, participants using the four and nine monitor configurations would adapt to the suicide bombers and create a defense especially for the use of destroying incoming suicide bombers. In general, the four and nine monitor configurations were able to successfully defend against the suicide bombers. However, the one monitor configuration generally would not be able to succeed in defending their base successfully even if a defensive force were constructed as they simply would not see the suicide bombers in time to react.

There were several times when one participant attacked the participant on the one monitor configuration and the participant on the one monitor configuration would not even notice until several building and units had been destroyed.

At the opposite extreme one participant on the one monitor configuration tried to surrender his game even though he had a sizable army left to battle with. The reason for his surrender is that he had forgotten that he had that army and did not see it until the proctor told him that he could not surrender until all his units were destroyed. As a side note, the proctor knew that the participant had the additional army because he saw it on the nine monitor configuration.

An interesting note on the nine monitor configuration is that participants were able to evaluate the battle field and realize if they were going to lose even before going into battle. For example, by looking and quickly summing all of one's own forces and all of the opposition's forces participants were able to determine if they would lose in an ensuing battle even before such battles began.

In general users on the larger monitor configurations had more insight into the map. Participants on the larger monitor configurations were able to see their entire base, the surrounding area, and quickly view the entire map faster than the one monitor configuration.

7.5 Conclusion

Through this experiment we found a number of things. First, we found that performance trends continued even with dynamic environments. Participants both scored higher and won the more games the larger the viewport size.

Second, we found that the larger displays helped with better strategies. Participants repeatedly reported and were observed to have better strategies with the larger viewport sizes. The most important point to make here is that participants' strategy types automatically changed from local focus to global focus.

Third, by recording mouse interaction we were able to empirically document how much participants virtually navigated at different viewport sizes. Previously in other experiments we observed qualitatively that participants tend to navigate virtually less with larger displays, but now we are able to quantitatively indicate exact amounts.

As Figure 35 shows, the larger the viewport size the less participants navigated. As a reminder to the reader, the mouse interaction recorded was only virtual navigation, not interaction with sprites (such as highlighting, attacking, etc.) As virtual navigation is simply a method for obtaining more information about the status of the geospatial visualization (the battlefield in this case) the less virtual navigation performed, the more participants could actually engage in their task of playing the game.

Here is a summary of the virtual navigation performed correlating to the performance of the participants:

The larger the viewport size, the greater the amount of data shown, the less virtual navigation performed and the higher the score and the number of wins.

We cannot conclusively say that the better scores with the larger displays were due more to the larger field of view or the decreased virtual navigation. The reason is that both the larger field of view and the decreased virtual navigation are both attributed to a larger viewport size.

7.6 Next Step

At this point we saw that an increased viewport size helped both with static and dynamic geospatial environments. However, we had only tested a viewport size of up to nine monitors. We decided that it would be prudent to test a larger viewport size in order to see how far the trend would continue. Although nine-monitors is usually considered a large display, we increased the size of the display to see how large of a display could still afford performance gains.

In addition, we wanted to know if curving the display would affect performance. Would the curvature add too much distortion to be helpful?

Chapter 8 Study 4 - Evaluation of Viewport Size and Curvature

The goal of this experiment was to see if the performance trends continued for displays larger than nine monitors and to see how curvature affects performance:

- Quantify the user performance benefits of increasingly larger displays (greater pixel-count) for geospatial tasks (Figure 40). We had previously only experimented with up to nine monitors. However, the question arises: Will the performance trends continue for even larger displays?
- Determine if the curvature of such large displays affects user performance for geospatial tasks (Figure 40). There are two reasons why curvature might affect performance. First, perception might be affected (see section 8.1). Second, as the curved display is physically closer, less effort may be required to get to a point in space.

Figure 40. Twenty-four monitor flat configuration (left) and twenty-four monitor curved configuration (right).

We presented this experiment at GI ’06 [131]. This experiment is the first of two experiments that we ran on our twenty-four monitor display. We present only the parts of the paper relevant to this dissertation.

8.1 Motivation

We hypothesized that user performance would improve with larger displays because users would have more data and more context visible at once, and afford efficient physical navigation using eye, head, and body movement. However, counterarguments could be that the large amount of visual information will overwhelm users, and that physical navigation will be too slow as compared to virtual navigation techniques such as pan and zoom. One could also argue that expanding the total screen size beyond the visual acuity of the eye wastes pixels [158].

We also hypothesized that curving the display would decrease the amount of time spent physically navigating, allowing for more time on the task. Users would only have to turn rather than walk to faraway pixels. Our main motivation for curving the displays was not to find an optimal curvature but to see if there exist any benefits of curving a display compared to keeping it flat. Therefore, we chose the same radius for all curved conditions (Figure 41). The following is an analysis of the interaction between visual acuity and display curvature, demonstrating how curving a display brings pixels into visual range.

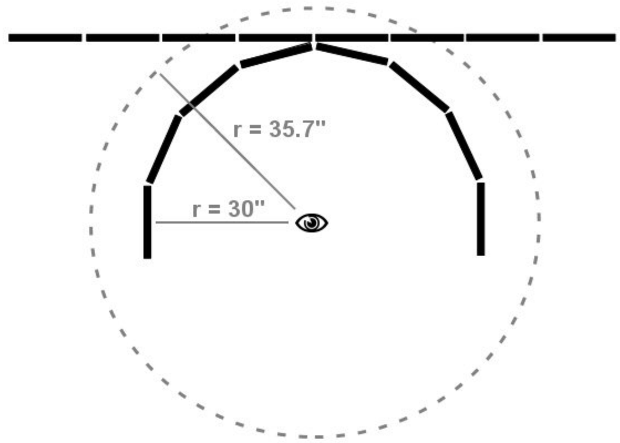


Figure 41: Visual acuity (dashed circle) and display configurations.

The display consisted of Dell 1740FPV color monitors that each had a maximum resolution of 1280×1024 and a dot pitch of 0.264mm×0.264mm. We calculated the maximum distance from which a user with normal visual acuity (20/20 vision) could resolve a 0.264mm pixel to be 90.7565cm or about 35.7 inches. This distance from the user is represented in Figure 41 by the dotted circle.

Consider what happens with flat displays. The maximum number of pixels that can be resolved on a flat display with only head and eye movements occurs when the user is standing unrealistically close to the display and looks to the left and to the right (setting aside the problem of the viewing angle for simplicity). This means the maximum display width such that all pixels are resolvable is 90.7cm×2 = 181.5cm (71.5 inches) or 6,875 pixels wide. Realistically, the user will not be standing against the display and as the user moves back fewer pixels will be resolvable. If the user is 30 inches from the center of the display, as they started in this experiment, then the number of resolvable pixels with head and eye movements is only 3,723. This is represented in Figure 41 by the intersections between the dotted circle and the eight straight blocks representing the flat display.

Now suppose we curve the display. The maximum resolvable distance remains the same (35.7 inches). If all users had perfect vision and the display had a radius no more than 35.7 inches then all pixels are resolvable with head and eye movements. In this experiment the display radius was set to a distance (30 inches) that accommodated slightly worse than 20/20 vision. Therefore, the entire width of our curved display (10,240 pixels wide) is resolvable. This is 2.75 times more resolvable pixels than with the flat condition.

8.2 Method

8.2.1 Hardware and Software Used

For the curvature variable, we curved the display on the horizontal plane such that the monitors would uniformly face the user. To do this the columns were faced inward such that the angle between each column was the same. Thus, the display was part of a uniform circle. For the experiment we used a modified version of the NCSA TerraBlaster (see section 4.6).

8.2.2 Tasks

We chose three different task types for all conditions: search, route tracing, and image comparison. We chose search and route tracing tasks based on our results from the earlier experiments. We chose an image comparison task based on expert geographer and cartographer advice. Participants performed two of each task type, an easy and a hard task, for a total of six tasks per condition. All tasks involved navigating extremely large aerial images at multiple scales. Similar to the other experiments, at the beginning of every task participants were started at the “best-fit” view of the map.

8.3 Experimental Design

The independent variables were viewport size, curvature, task type, and task difficulty. We chose three viewport sizes: one monitor, twelve monitor, and twenty-four monitor conditions. For the one monitor condition the TerraServer application was simply resized to fit one of the middle monitors. For the twelve monitor condition the application was expanded to half of the display such that it filled a 4×3 matrix of monitors. For the curvature variable, we chose two curvatures: flat and a curved with radius equal to 30 inches (Figure 41). In general, one can create different curvatures by adjusting the radius. We tested five of the six conditions (Table 5). The one monitor curved condition is not applicable since one cannot curve a single monitor.

Table 5: The five conditions tested

	Flat	Curved
1 monitor	✓	
12 monitors	✓	✓
24 monitors	✓	✓

Viewport size and curvature were between-subject variables because of the time it takes to reconfigure the display. The order of tasks within each task type was counterbalanced using two 4×4 Latin Square designs, where one dimension represented the task type and the other dimension represented four of the eight participants. Each task type had one easy and one hard task. Within each task type (e.g. the two search tasks), half of the participants would get the easy task first and the other half would get the harder task first.

For each condition we used eight participants for a total of 40 participants. All participants were undergraduate or graduate students. The majority of the participants were computer science majors with a few exceptions. The average age of the participants was 25 with a range between 21 and 31 years old. Twenty-seven of the participants were male and 13 were female. All had normal to corrected-normal vision. All participants reported having daily use with computers.

8.4 Results

8.4.1 Completion Time

Task completion time was measured for both the route tracing and search tasks. For the comparison tasks participants were always given 5 minutes, therefore completion times for the comparison tasks were not analyzed. Times for participants that timed out after 5 minutes were recorded as 5 minute task completion times. One participant was thrown out as an outlier, since that participant timed out on every task, regardless of difficulty level.

8.4.1.1 Overall Completion Times

We performed a 3-way ANOVA. Analysis of variance showed a main effect for display configuration ($F(4,136)=3.52$, $p=0.009$), task type ($F(1,136)=134.9$, $p<0.001$), and task difficulty ($F(1,136)=15.39$, $p<0.001$). Search tasks were significantly faster than route tracing tasks and easy tasks were significantly faster than hard tasks. Post-hoc analysis of the display configurations showed a statistically significant difference ($p<.05$) between several of the display configurations.

Figure 42 shows the results of the post-hoc analysis. Non-overlapping confidence intervals are statistically significant at the alpha level of 0.05. All large display conditions, except for the twelve flat condition, are statistically faster than the one monitor condition. Furthermore, the twenty-four curved condition is faster than the twelve flat condition.

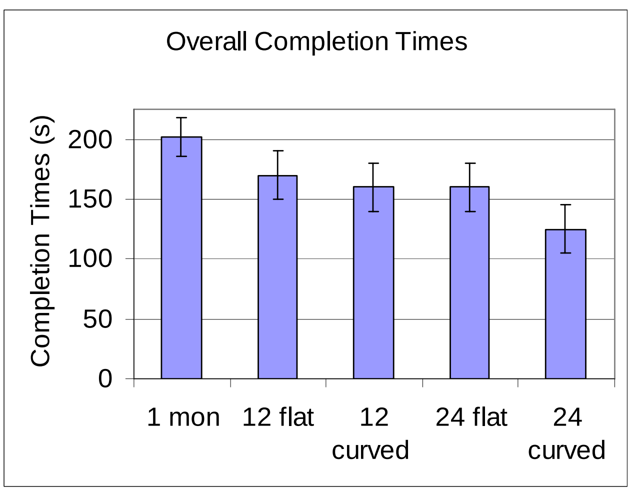


Figure 42: Performance times in seconds of all display configurations. Non-overlapping error bars indicate statistical significance.

Figure 42 shows the general trend that increasingly larger viewport sizes and curved displays reduce performance time. However, an interesting observation is that by curving the twelve monitor condition (158.5s) the performance times roughly equated that of the twenty-four flat condition (158.3s). However, by curving the twenty-four monitors the performance time again decreased for the twenty-four curved condition (124s).

Analysis of variance also resulted in non-significance for difference between flat (157s) and curved (143s) conditions. The one monitor condition was not included in the analysis as it did not have a curved counterpart.

8.4.1.2 Task Specific Completion Times

Since, 48% of participants for the hard route task and 26% of the hard search task timed out regardless of the display condition, the hard tasks were not analyzed in this section. This section only shows the results for the easy tasks.

As the experimental design was an incomplete factorial design (Table 5) we analyzed the easy tasks by performing two different analyses of variance. The first analysis was a mixed-model three-way ANOVA where the curvature and viewport size were between subject and the task type was a with-in subject factor. Note, here task difficulty is eliminated as a factor because hard tasks are not analyzed. This first ANOVA did not include the one monitor condition, because it is not relevant to the curvature variable.

The resulting analysis showed that there were main effects for viewport size, curvature, and task type. There was also an interaction between the task type and viewport size ($F(1,27)=10.26$, $p=0.003$). For viewport size, we found that participants performed faster on the twenty-four monitors (112 seconds) than the twelve monitors (145 seconds) ($F(1,27)=7.18$, $p=0.012$). For curvature we found participants performed faster on the curved displays (111 seconds) than the flat displays (146 seconds) ($F(1,27)=7.82$, $p=0.009$) (Figure 43).

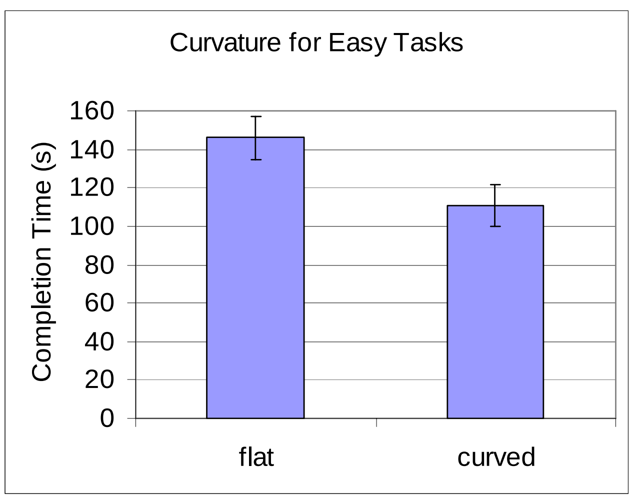


Figure 43: Average completion times in seconds for easy tasks on twelve and twenty-four monitor curvature conditions

Lastly, for the task type we found that that the search tasks were faster than route tasks ($F(1,27)=186.1$, $p<0.01$).

We used Fisher's protected t-test as a post-hoc comparison to further investigate the viewport size and task type interaction. For the route task we found that the twenty-four monitors (178 seconds) were faster than the twelve monitors (251 seconds), whether flat or curved ($p=0.004$). The search task showed that the twenty-four monitors (46 seconds) was not statistically different than twelve monitors (38 seconds) ($p=0.58$) (Figure 44).

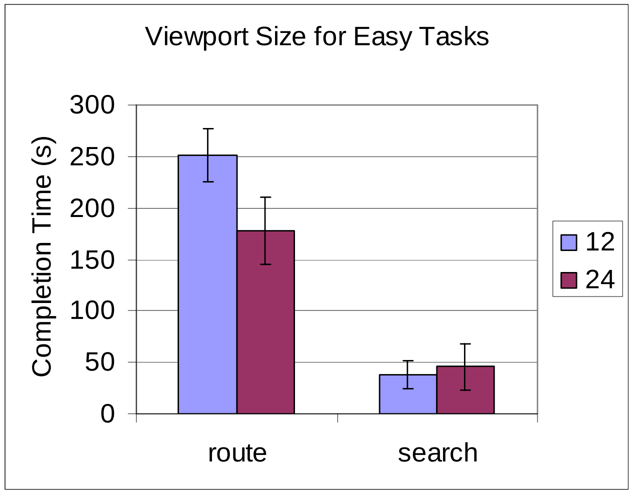


Figure 44: Average completion times in seconds for easy search and route tasks on twelve and twenty-four monitor viewport sizes

The second analysis was a mixed design two-way ANOVA that took into account the one monitor condition; the variables were display configuration (i.e. one monitor, twelve flat, twelve curved, 24 flat, and 24 curved) and task type (i.e. easy route and easy search). The result was an interaction between the task type and display configuration ($F(4,34)=4.24$, $p=0.007$).

In summary, we did not find an interaction between curvature and viewport size. However, we did find an interaction between viewport size and task type. This indicates that curvature helped with performance times regardless of viewport size and that viewport size helped more with the route task than the search task.

This difference between tasks could be explained due to the nature of the tasks themselves. The route task was very long and utilized the wide screen space, whereas the search task involved a square area, fitting more easily in the twelve monitor display with little zooming.

8.5 Observations

In general, we observed differences in how users interacted in the different conditions. First considering the viewport size, there was a striking difference between the one monitor condition and the larger display conditions. In the one monitor condition users tended to use more virtual navigation than those in the flat twelve and twenty-four monitor conditions. Specifically, users zoomed in and out significantly more on the one monitor condition to regain their overview of the task area. In the larger display sizes users tended to use more physical navigation. This included standing up, walking, leaning towards the sides of the display, and head turning. Often the user's strategy for accomplishing the task was the same (e.g. serial searching), but the technique was applied with virtual navigation in the one monitor configuration and with physical navigation in the larger configurations.

Considering curvature, users physically interacted with the largest displays in different ways. For example, on the flat twenty-four monitor condition more users would either stand or walk; in that condition, five out of eight users stood up at least once. In the curved twenty-four monitor condition, however, users would turn their heads or their body. It may be because of this change in physical navigation that performance times were faster when the display was curved.

Even though the twenty-four monitor display was physically large, most participants did not stray far from their stool, despite clear instructions during the tutorial that they may feel free to move around. One possible explanation is that participants could only interact with the keyboard and mouse, and if participants moved away from their seat then they would have to either move back to the keyboard or move the rolling stand with them. Although the wheeled stand provided in this experiment brought mobility to the keyboard and mouse, it is clear that there may be a need for alternate input devices.

Furthermore, users changed their area of focus less frequently on the flat twenty-four monitor condition than those on the curved twenty-four monitor condition. Often users on the flat display would focus on nine or twelve monitors at a time. Sometimes their focus area would shift from the left side of the display to the right side of the display over the course of the task. However, most users preferred to sit (even if they stood at some point) and use the center of the display as their focus area. On the curved condition users would switch their area of focus more often by a quick turn of the head. Therefore, it appears that curving the display results in the users making use of a greater percentage of the available pixels more frequently.

8.6 Conclusion

There were several important conclusions that we found in this experiment. First, we verified that viewport size improves performance time based on a per task basis. There appears to be a certain zoom level that is optimal for a particular task based on the amount of detail needed to complete the task.

Second, the size and shape of the display play a role. For example, the route task covered a large geography area, but somewhat linear and horizontal. The large and wide twenty-four monitor display probably correlated well with the size and shape of the task data. Also, its linear structure was easy for users to virtually navigate, even with the small one-monitor screen.

However, the search task data was square in shape and did not cover as large a geography area, and required full 2D navigation of the entire space. Hence, the larger display sizes had the advantage of minimal virtual navigation, while the one monitor screen size required a lot of complex virtual panning and zooming. The twelve and twenty-four monitor display sizes probably had similar performance due to the square shape of the data, which did not need to take advantage of the wide aspect ratio of the twenty-four monitor display. The observed reduction in virtual navigation and increase in physical navigation correlates to improved user performance. Combining increased visual imagery with physical navigation was beneficial in this case.

Third, the curved displays improve performance over flat displays regardless of viewport size. For the easy tasks, curvature performance was approximately 30% faster than flat. Of all five display conditions, user performance was the best on the curved twenty-four monitor condition. Curvature improved performance probably because users could better utilize the left and right outermost pixels on the display (as shown in section 8.1). In the flat twenty-four monitor condition, for example, users were at least 4 feet away from the furthest pixels. However, in the curved twenty-four monitor condition the user was never more than 2.5 feet from any given pixel.

Fourth, physical navigation changes from standing and walking to turning when the display is curved were observed. We observed that the physical navigation was different on the flat and curved conditions. The change from standing and walking around the flat display to turning in the curved display supports our visual acuity hypothesis. When combined with the fact that curved displays improved performance, this indicates that this type of physical navigation was more efficient for users and better enabled them to visually access and process the imagery.

8.7 Next Step

At this point we had learned that performance time with large displays was affected by a number of things beside viewport size. First, a larger viewport size allows more information to be viewed at once, which allows for greater perception at once. This greater perception of information helps in two ways:

1. By being able to see more information at once, more information can be analyzed and perceived faster (validating Pirolli's work [104]). The result of this includes better task strategies and better comprehension of the overview and details.
2. Less virtual navigation is needed to see all of the desired space. The byproduct of less virtual navigation to perceive a given space is greater comprehension of the space in a given time. By not needing to virtually navigate as much, less cognitive effort is expended to recreate a mental map of the space [121].

Second, there appears to be an optimal zoom level, or scale, for particular tasks. Not all tasks need the same amount of detail; therefore, not all tasks have the same optimal zoom level. It appears that being able to see the maximum amount of details pertaining to the task for a particular task is where viewport size helps the most.

Third, it appears physical navigation is also a limiting factor. From Study 4 we found that physical navigation also plays a key role in performance time. Study 4 especially showed that when pixels are more easily accessible, such as with a curved display, then more of the display can be used.

It appears that with physically large displays, such as with the twenty-four monitor display, physical navigation plays a larger role. As a natural consequence, we decided to proceed with a final capstone experiment that would particularly focus on understanding how navigation, both physical and virtual, play a role in performance time along with space scale.

Chapter 9 Capstone Experiment

The goal of this final experiment was to understand how navigation and the space-scale model are realized in a setting with incremental display size. The main purpose of the experiment was to understand how behavior and performance time change with actual tasks that one might perform with an information visualization. The independent variables were:

1. Viewport size
2. Task type
3. Task scale (space scale of tasks)

The dependent variables were:

1. Performance time (or number of insights for the insight task)
2. Physical navigation (i.e. participant's position in 3D space)
3. Virtual navigation (i.e. mouse interaction)

We chose not to test a curved display even though we found that it is generally more efficient than a flat display for a number of reasons: First, we wanted to measure how well people could use a flat display without being "tethered" by an input device. Second, we wanted to measure physical navigation with the more traditional display that more of the research community is familiar with: a flat display.

In order to simplify the experiment participants were tested on different widths of a display by column number (see Figure 45). For example, if a participant were tested at the four column condition, then only the first four columns would be used and columns five through eight would be left unused. If a participant were being tested at the eight column condition then all columns, one through eight, would be used.

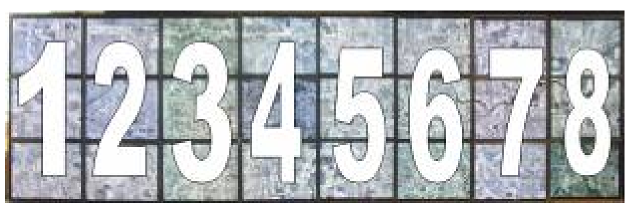


Figure 45. Image showing how the display was artificially separated into different columns. The total resolution of the display is 10240 X 3072. The physical dimensions of the display were roughly 9 feet (2.7 m) by 3.5 feet (1 m).

For the first two tasks, we had a with-in subject design. All participants repeated the first two tasks on all of the column conditions. For the last two tasks, we had a between-subject design. For the last two tasks, each participant only did tasks on one column condition. The reason for having the between-subject design was that the last two tasks were more complicated in nature and thus took longer to complete. All participants did all four tasks.

9.1 Experimental Design

9.1.1 Hardware and Software Used

The display used for the experiment was made up of twenty-four seventeen inch LCD monitors and twelve GNU/Linux computers in an 8×3 matrix. Each monitor was set to the highest resolution of 1280×1024. Each computer powered two monitors. We removed the plastic casing around each monitor to reduce the bezel size (gap) between monitors.

For the experiment we used a modified version of the NCSA TerraServer Blaster. TerraServer Blaster is an application that views images from the TerraServer database maintained by the US Geological Survey. The images are multi-scale in nature in that one can zoom in sufficiently to shadows of people or zoom out to see all of the Houston metropolitan area (the geographic area used in the experiment) at once.

9.1.2 Interaction

All interaction with the display by the participants was performed using a gyro mouse. A gyro mouse is a wireless mouse that works in a 3D environment and does not require a flat surface to function. The gyro mouse was used to not encumber participants as they walked around (see Figure 46.a). To track physical navigation in 3D space, a VICON system was used. Figure 46.a and Figure 46.b show users wearing hats with reflective beads that are tracked by cameras.

Figure 46. a) Image showing a participant using the gyro mouse with the display. The gyro mouse is enlarged in the red square. b) An image showing the hat used to track users' position.

All participants stood or walked for the experiment for the purpose of seeing maximum potential physical navigation. No chairs were provided during the experiment as the chairs would limit the amount of physical navigation a participant might perform. Chairs were provided during breaks between tasks.

Zooming was performed relative to the mouse cursor. In other words, the position of the cursor became the focal point in which users zoomed. Panning was performed by clicking a mouse button then moving the cursor. For example, if the cursor was over a particular house and the user held down a mouse button and moved the cursor to another position on the screen, the underlying viewport would move with the cursor so that the cursor remained over the same house but the user's view of the map would have shifted (e.g. the house of interest might be left of where it was and more of the map on the right would be revealed).

9.1.3 Participants

The experiment used 32 participants with 10 females and 22 males. Approximately half the participants were from the local town and the other half from a variety of majors from the university. The ages of the participants ranged from 24 to 39 with an average age of 28.

9.1.4 Experimental setup

The experiment consisted of four tasks: basic navigation, search, pattern finding, and insight finding (based on [126]). The first two tasks, basic navigation and search, were a with-in subject design in which all 32 participants performed on all eight column widths. Participants started at eight different starting points using a Latin Square design.

For the second two tasks, pattern finding and insight finding, were between subject designs. Only the 1, 3, 5, and 7 column conditions were used to increase statistical power by having eight participants in each cell instead of only four.

So, the task variable had four levels (the four tasks), task scale had two levels for the navigation task (medium and low), three levels for the search and pattern task (high medium, and low), and zero levels for the insight task. For the navigation and search tasks participants had eight repetitions for each task scale. The pattern task and insight task had zero repetitions (as they were between subject).

A general tutorial time of about 5-8 minutes was given for each participant before they began. After the tutorial the participant would perform the first task, basic navigation, on their starting column condition. After that, they would perform the second task, basic search, on the same column condition. After the completion of the search task they would move to the next column condition. After the first two tasks had been performed on each of the column conditions the participant would then be assigned to a single column condition to perform the last two tasks.

Each task began with the overview/best-fit of the map (see Figure 47). This preserved the aspect ratio of the base map so that each column showed the same amount of coverage of Houston, but at different amounts of detail.

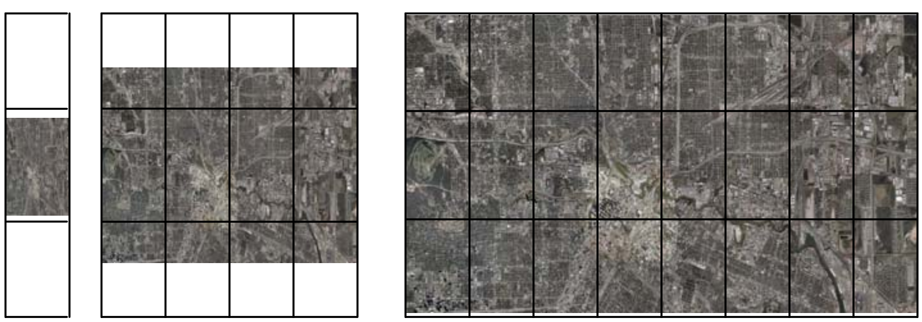


Figure 47. Example of best-fit of the geographic base map for the one column, four column, and eight column conditions without the houses visualized.

It should be pointed out that as participants zoomed in on viewport sizes that did not completely fill the display horizontally (e.g. the one column condition) that more of the viewport was filled with the map. In practicality, it only took a few zooms to fill the one column condition horizontally.

Figure 48 shows how the one column condition might start out by only seeing a small overview and not filling the display. The blue outline of the one column viewport shows how at the "best-fit" start that only the center monitor is used. However, as participants zoom in for greater detail more of the display is used. The corresponding viewports are shown as the middle and right images.

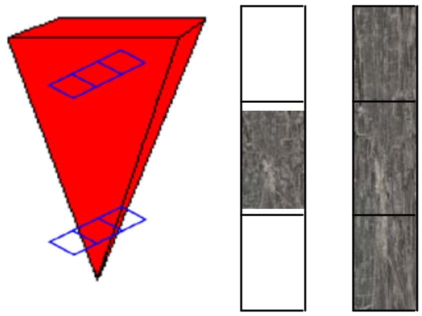


Figure 48. Example of why the one column condition does not use the entire display at the beginning of each task with the "best-fit" view. The middle image corresponds with lower viewport shown in the space-scale diagram and the right image corresponds with the top viewport shown in the space-scale diagram.

9.2 Data and Visualization Explanation

The data used was data mined from an online real estate website. Thousands of houses in the Houston area were used. The data was then filtered by only showing houses between $30,000 and $300,000 inclusively, which resulted in over 3,500 houses.

A visualization of the houses was created based on semantic zooming. In this example, Figure 49.a shows only the geospatial position and the bar charts of the prices of the houses in Houston. However, Figure 49.b, another level of semantic zooming, shows the geospatial position, the bar charts of the prices, and the actual text of prices at a deeper scale. The semantic zooming scheme used was from the most overview to the most detailed views. Information was not lost, only gained by zooming in.

The following zoom levels were used for different semantic views:

- Zoom $\text{level}_{0.0}$ to less than zoom $\text{level}_{0.2}$ ($\text{level}_{0.0\text{-}0.2}$): Used to show geospatial position of houses only (see Figure 49.a).
- Zoom $\text{level}_{0.2}$ to less than zoom $\text{level}_{0.4}$ ($\text{level}_{0.2\text{-}0.4}$): Used to show geospatial position and price (see Figure 49.b).
- Zoom $\text{level}_{0.4}$ to less than zoom $\text{level}_{0.6}$ ($\text{level}_{0.4\text{-}0.6}$): Used to show geospatial position, price, and number of bathrooms.
- Zoom $\text{level}_{0.6}$ to less than zoom $\text{level}_{0.8}$ ($\text{level}_{0.6\text{-}0.8}$): Used to show geospatial position, price, number of bathrooms, and number of bedrooms.
- Zoom $\text{level}_{0.8}$ to zoom $\text{level}_{1.0}$ ($\text{level}_{0.8\text{-}1.0}$): Used to show geospatial position, price, number of bathrooms, number of bedrooms, and square feet.

Figure 49. a) Image showing houses at an overview scale(between zoom level$_{0.0}$ and zoom level$_{0.2}$) – only showing a bar chart of normalized price values and geospatial position. b) Image showing the same houses at a deeper scale (between zoom level$_{0.2}$ and zoom level$_{0.4}$) - actual text is also shown.

As explained in Chapter 3 (explanation of the space-scale model), the space (or area) in space scale increases the more one zooms in until zoom level$_{1.0}$. As a natural result, the larger the viewport size needed to accommodate all details at once in geospatial visualizations. For example, all the geographic positions of the all the houses can be displayed on a single column of monitors for the experiment. However, to see all of the houses with the amount of square feet shown, one would need a 100-monitor display.

9.3 Tasks

Each task had three levels along the space-scale diagram: high, medium, and low, except for the navigation task which only had two. A "high" task was considered an overview task in which only geospatial position of the data, not any of the details themselves, was taken into account. A "medium" task had some higher-level details required to complete the task, such as the price of a house. A "low" task was in which some lower-level details were required to complete the task, such as the square footage of a house. Figure 50 shows a visual representation of the different scales of the tasks. Columns are roughly labeled about where the "optimal" display size might correspond per task scale.

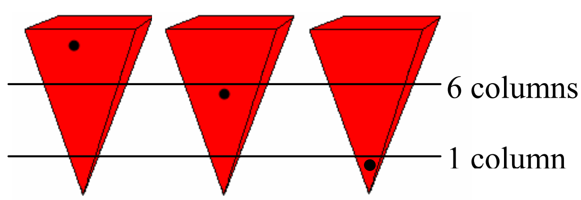


Figure 50. A visual representation of different scales of the tasks. The first image shows that the "low" task, the second image shows the "medium" task, and the third image shows the "high" task.

In terms of zoom level, the following shows the correlation between zoom level and the task level:

- "High" task: zoom level$_{0.0\text{-}0.2}$
- "Medium" task: zoom level$_{0.2\text{-}0.4}$

- “Low” task: zoom level$_{0.8\text{-}1.0}$ (zoom level$_{0.6\text{-}0.8}$ for the pattern finding task)

The navigation task was created as a benchmark against the other tasks. Its purpose was to determine the minimal time it would take a person to access different levels of details for different display sizes.

For the navigation task, a single house was shown on the display. The participant was asked to verify that he could see the house before proceeding. The reason for this verification was to ensure that the participant was not being asked about their ability to find the house. After verifying the presence of the house he was then asked for either its price or square footage (two different subtasks at different task scales). No overview task (less than zoom level$_{0.2}$) of indicating geospatial position was used because the participant was required to see the geospatial position of the house before the task began in order not to test perception and only navigation. The task was complete when the participant had spoken aloud the correct corresponding price or square feet of the house.

The search tasks involved searching, or finding, particular houses that had particular attributes. For example, a “medium” subtask (zoom level$_{0.2\text{-}0.4}$) required participants to find any house with a particular price range. An example is, “Find a house anywhere in Houston between $100,000 and $110,000.”

Pattern finding tasks followed the same model as the search tasks. Participants were asked to find a particular pattern for particular scales. Particularly, participants were asked to find the densest cluster of houses (zoom level$_{0.0\text{-}0.2}$), the pattern of the prices of the houses (zoom level$_{0.2\text{-}0.4}$), and the pattern of the bedrooms of the houses (zoom level$_{0.6\text{-}0.8}$). In order to measure only performance time and not accuracy participants were asked to continue searching for the correct pattern until they reported the correct pattern.

The reason semantic zoom levelsl$_{0.6\text{-}0.8}$ were used instead of zoom levelsl$_{0.8\text{-}1.0}$ was due to a time constraint. As the appropriate viewport size for finding patterns between zoom levelsl$_{0.8\text{-}1.0}$ was so large the time it took was a considerable amount of time to complete on even the eight column configuration (all twenty-four monitors) that such a task would introduce additional fatigue for the participants.

The open-ended insight task followed Saraiya, et al.’s [126] model of evaluating different information visualizations based on the depth of insights. However, instead of evaluating different information visualizations, different display sizes were evaluated. For this particular task participants were given a mobile lecture stand with wheels on which to write insights. Figure 46.b shows a participant using the mobile stand.

Unlike the other tasks that each recorded performance time, the open-ended insight task involved participants writing as many insights about the data as possible in ten minutes. Participants were told that each insight would be scored from 1 to 4 where 4 being the most insightful to 1 being the least insightful. An insight was defined solely as “an observation about the data.”

9.4 Quantitative Results

This section reports the quantitative results of the experiment. For the first three tasks (navigation, search, and pattern finding) the performance times were analyzed.

For the insight task the papers marked by the participants were graded for depth of insights by two graders that were familiar with the data. However, after analysis of variance was performed on the insight grades non-significant results were found due to high variance in the answers. However, a general trend was found that the one column did not find as many overview insights because it could not see all the houses on the map well enough at an overview level to easily form an accurate mental model. These results might be explained by the physical/virtual navigation of the task.

After performance analysis is shown, virtual navigation and physical navigation analyses are explained.

9.4.1 Performance Time Analysis

In order to analyze performance results we ran a two-way ANOVA on performance times with column widths, and tasks as the variables. Our results found only a main effect for column widths ($F(1,1324)=20.56$, $p<0.01$) and task type ($F(2,1324)=77.05$, $p<0.01$). The space-scale of the tasks was not included in this ANOVA as the different tasks used different scales.

In other words, we found that there was a statistical significance in column widths and with task type. With the task type we performed a post-hoc Tukey HSD analysis that showed that the different task types were all in different groups.

As each task type was statistically different from each other we performed individual ANOVA's for each of the tasks.

9.4.1.1 Navigation Task Performance Results

For the navigation task we performed a two-way ANOVA with the task scale and column widths as the variables. We found a main effect of the task scale ($F(1,508)=98.1$, $p<0.01$) indicating that the two different scales of tasks were different from each other, a main effect of column width ($F(1,508)=118.9$, $p<0.01$), and an interaction between the space scale of the task and column width ($F(1,508)=4.09$, $p=0.04$).

Figure 51 shows the general trend of navigation performance results. It should be pointed out that the low task (zoom $\text{level}_{0.8\text{-}1.0}$) on the six column condition is an outlier due to the target being displayed across a bezel. Targets were placed in the space randomly, however only the target on the low task on the six column condition occurred across the bezel. The main reason for the increased in performance time can be attributed to the additional time it took participants to pan the viewport so that they could clearly read the text that crossed the bezels. Additional information about bezels and their problems and solutions is discussed by Mackinlay, et al [83].

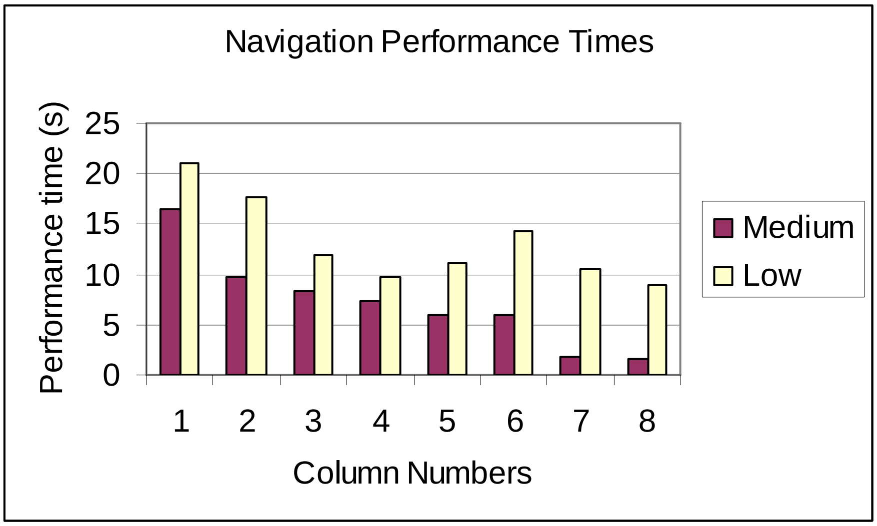


Figure 51. Performance averages for the navigation task.

9.4.1.2 Search Task Performance Results

Another two-way ANOVA with the same variables was performed for the search task and resulted in similar results of a main effect of task scale $F(2,762)=130.13$, $p<0.01$), a main effect of column width ($F(1,762)=38.18$, $p<0.01$), and an interaction between the task scale and column width ($F(2,762)=9.34$, $p<0.01$). Post-hoc analysis using Tukey HSD found that the performance times of the different scales were all different groups.

Figure 52 shows that the performance times of the search task largely depended on both the task scale and the column width. For the high task (zoom $\text{level}_{0.0\text{-}0.2}$) after the first column condition, the performance time appears roughly uniform. However, for the medium task (zoom $\text{level}_{0.2\text{-}0.4}$) and the low task (zoom $\text{level}_{0.8\text{-}1.0}$) there are different patterns. The medium task shows almost a straight line between columns one and six then a linear drop off thereafter. The low task shows the opposite; with almost a linear drop off between columns one and six and almost a straight line thereafter.

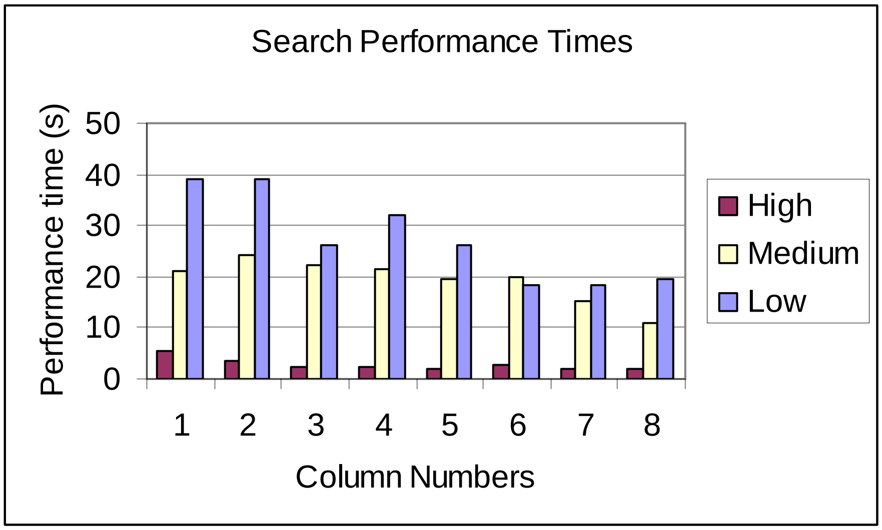


Figure 52. Performance averages for the search task.

It is obvious that with the task being held constant and the column conditions and scales of the task changing that there must be other factors that are affected that change the performance behavior. These differences in behavior between the different scales of the task are attributed to various factors including semantic zooming, physical navigation, and virtual navigation. This analysis will be discussed in further detail in the next chapter.

9.4.1.3 Pattern Finding Task Performance Results

Another two-way ANOVA with the same variables was performed for the pattern task and resulted in similar results of a main effect of task scale ($F(2,90)=89.65$, $p<0.01$), a main effect of column width ($F(1,90)=3.53$, $p=0.06$), and an interaction of task scale and column width ($F(2,90)=3.22$, $p=0.044$). Post-hoc analysis using Tukey HSD found that the performance times of the low task (zoom $\text{level}_{0.8\text{-}1.0}$) was in a different group from the high (zoom $\text{level}_{0.0\text{-}0.2}$) and medium (zoom $\text{level}_{0.2\text{-}0.4}$) tasks.

Figure 53 shows how the different scales of the pattern task affected the performance times. The high (zoom $\text{level}_{0.0\text{-}0.2}$) and medium (zoom $\text{level}_{0.2\text{-}0.4}$) tasks appear to have approximately the same performance curve behaviors of a straight line. Both tasks were performed with little or no zooming and resulted in the same performance curve behaviors.

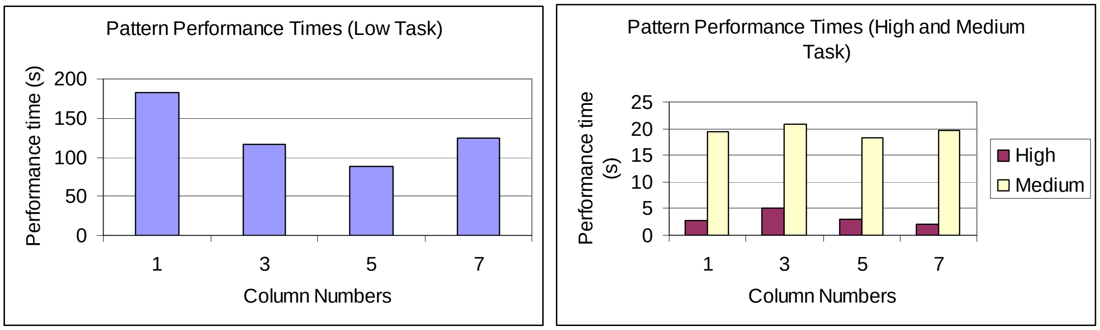


Figure 53. Performance averages for the pattern task. Charts were separated to help with readability of the high (zoom level$_{0.0\text{-}0.2}$) and medium (zoom level$_{0.2\text{-}0.4}$) tasks as the low task (zoom level$_{0.6\text{-}0.8}$) had drastically different performance times.

On the other hand, the low task (zoom level$_{0.6\text{-}0.8}$) had a different performance behavior. It is unclear from the data whether the performance curve is a decrease in performance time from the one to three column conditions then a straight line or an almost linear decrease in performance time followed by an increase in time at the seven column condition.

9.4.1.4 Performance Analysis Conclusions

Larger viewport sizes can drastically decrease performance times. For example, on the medium navigation task (zoom level$_{0.2\text{-}0.4}$), performance time was reduced more than ten times from 16.3 seconds on the one column condition to 1.5 seconds on the eight column condition. Another example is the low search task (zoom level$_{0.8\text{-}1.0}$) where performance was reduced more than two times from 39 seconds on the one column condition to 19 seconds on the eight column condition.

As section 9.4.2.1 will explain, there appears to be a stepwise linear pattern in the performance curves. In other words, there appears to be different areas that have a linear performance curve followed by a different linear performance directly after. These different linear performance can be explained by other factors influencing performance beyond viewport size.

The next two subsections show how the virtual and physical navigation parts of the task play a key role in driving up the time it takes to perform the task on the seven column condition.

9.4.2 Virtual Navigation Analysis

In an effort to better understand what participants' behavior was for virtual navigation we recreated their virtual movements. We did this by creating scripts that took the participants' raw virtual navigation data that was recorded and analyzed their zooming and panning behavior. We then took the resulting analysis and ran statistics on them. In this section we report a few of the more interesting results.

In understanding these virtual navigation results it is important for the reader to understand why participants needed to virtually navigate. First, for each task there was a particular scale or zoom level (e.g. zoom level$_{0.2\text{-}0.4}$) that they had to navigate to see the necessary details for the tasks (e.g. price of the houses). Second, the participants would sometimes pan to move around the space. Panning was never required as moving around space can also be accomplished by a series of zoom movements (see [51]).

To understand how virtual navigation differed generally we performed a series of two-way ANOVA's on column widths and task types. First, we wanted to see how the number of zooms that a person performed was affected by column widths and task types. We found a main effect of task type ($F(3,1400)=416.2$, $p<0.01$), a main effect of column width ($F(1,1400)=34.8$, $p<0.01$), and an interaction of task type and column width ($F(3,1400)=2.4$, $p=0.06$). Post-hoc Tukey HSD analysis shows that the different tasks were all different groups.

Another analysis of interest is the number of pans performed. The reader should note that the number of pans is only mouse movement that actively moves the viewport in space. It is not inactive mouse movement that is used to reposition the cursor without moving the viewport. The resulting ANOVA showed a main effect of task type ($F(3,1400)=301.3$, $p<0.01$), a main effect of column width ($F(1,1400)=63.86$, $p<0.01$), and an interaction of task type and column width ($F(3,1400)=17.22$, $p<0.01$). Post-hoc Tukey HSD analysis shows that the insight task was in a different group from the other tasks.

Performing a similar ANOVA, we wanted to see how the lowest scale that a participant zoomed to during the task was affected. We found a main effect of task type ($F(3,1400)=48.4$, $p<0.01$), a main effect of column width ($F(1,1400)=51.9$, $p<0.01$), and an interaction of task type and column width ($F(3,1400)=43.7$, $p<0.01$). Post-hoc Tukey HSD analysis shows that the different tasks were all different groups.

Although the number of zooms and the lowest scale zoomed to are related they both reveal different things. First, the number of zooms are for both zooming in and out and reveals how much zooming in *and* zooming out participants performed. It reveals in conjunction with the number of pans how much moving around the participants performed in space and scale.

The lowest scale analysis shows what the lowest scale the participants' zoomed into was. This is important because it allows us to understand how much the scale was of importance to the virtual zooming performed.

Another interesting analysis is to find out how participants' performance time correlated to the number of zooms and the number of pans. In effect, the question is how participants' movement in space scale affected their performance time. The result of a two-way ANOVA with performance and the number of zooms and the number of pans as variables shows a main effect of the number of zooms ($F(1,1400)=970.37$, $p<0.01$), a main effect for the number of pans ($F(1,1400)=267.37$, $p<0.01$), and an interaction of the number of zooms and the number of pans ($F(1,1400)=41.57$, $p<0.01$).

This indicates that the amount of movement through space scale has a strong correlation to performance time. This will become increasingly clear as each individual task is explained.

We also performed a number of other analyses, such as how column width and task affects the highest scale navigated to, the average scale, the last scale, and standard deviation. However, these additional analyses do add any additional insight into the participants' virtual navigation and are not discussed here.

Individual tasks are reported for the rest of this section.

9.4.2.1 Navigation Task Virtual Navigation Analysis

Specifically for the navigation task we performed a number of additional analyses. First, we performed a two-way ANOVA correlating column widths and task scale to the number of zooms. We found a main effect of task scale ($F(1,508)=198.8$, $p<0.01$), a main effect of column width ($F(1,508)=144.6$, $p<0.01$), and an interaction of task scale and column width ($F(1,508)=9.5$, $p<0.01$).

Figure 54 clearly shows two things. First, the larger the viewport size the fewer the number of zooms performed. Second, task scale is also important in understanding the number of zooms. The level of detail shown increased as the viewport size increased to the point that no zooms were necessary for the medium task (zoom $level_{0.2-0.4}$), this was not the case for the low task (zoom $level_{0.8-1.0}$). Clearly, when not all the detail that is necessary is shown then one must zoom in to see it relating back to the importance of semantic zooming.

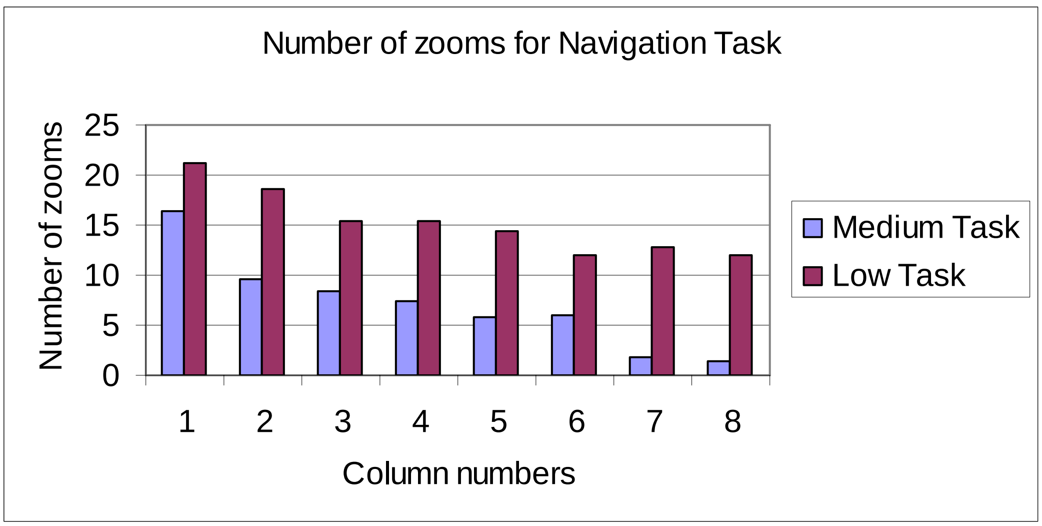


Figure 54. Average number of zooms for the navigation task.

We then performed a similar two-way ANOVA for the amount of panning. We found a main effect of task scale ($F(1,508)=10.1$, $p<0.01$). The reader may notice the outlier for the low task (zoom $level_{0.8-1.0}$) at the six column condition (see Figure 55). This correlates to the additional amount of panning required to move the viewport so that the target did not lie on the bezel. This spike in additional panning is the same spike seen in performance in Figure 51.

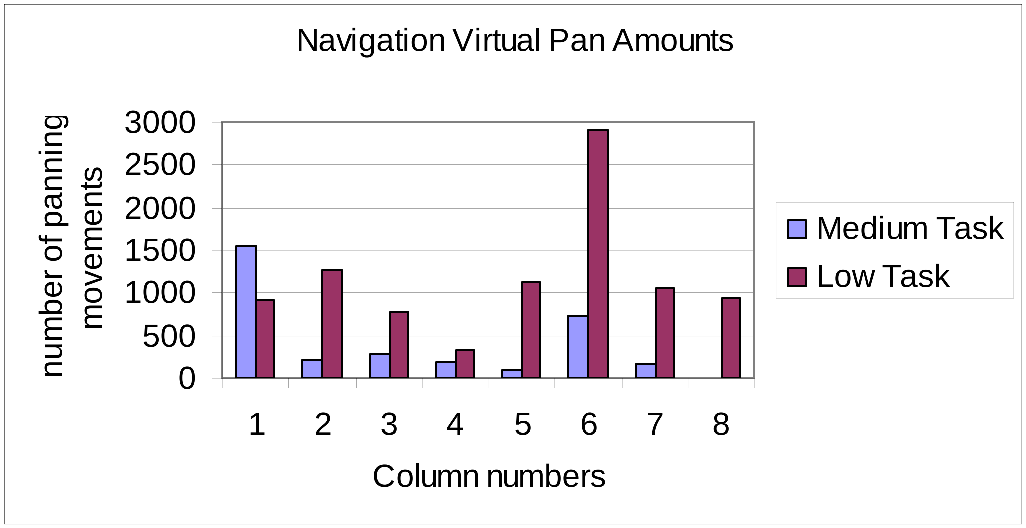


Figure 55. Average number of virtual panning for the navigation task.

One might also notice that no panning was performed on the medium task (zoom level$_{0.2-0.4}$) on the eight column condition. This is similar to how there was no zooming performed either. As all the detail was needed to perform the task could be seen at the beginning of the task, no virtual navigation was performed.

Performing a similar ANOVA for the lowest scale that participants zoomed to we found a main effect of task scale ($F(1,508)=858.4$, $p<0.01$), a main effect of column width ($F(1,508)=7.9$, $p<0.01$), and an interaction of task scale and column width ($F(1,508)=8.5$, $p<0.01$).

Figure 56 shows that the semantic threshold needed to see the necessary detail is important in understanding how much virtual navigation is required. The medium task (zoom level$_{0.2-0.4}$) did not require as low a zoom level as the low task (zoom level$_{0.8-1.0}$). Consequently, participants did not have to be as exact in the amount of zooming performed.

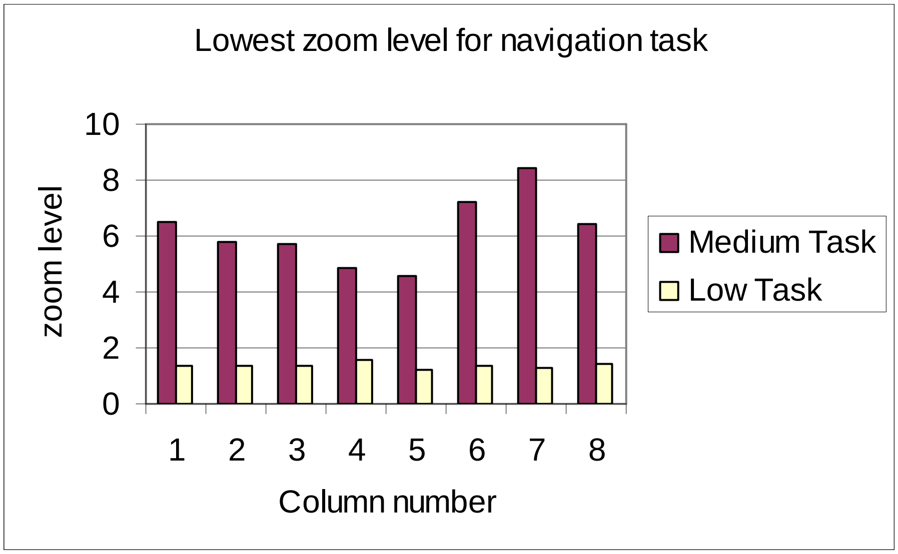


Figure 56. Average lowest zoom level for the navigation task. Note that the zoom level is not normalized between 0.0 and 1.0.

Performing a similar ANOVA on performance time with the number of zooms and the number of pans as variables shows the same trend as before: a main effect of the number of zooms ($F(2,508)=585.5$, $p<0.01$), a main effect of number of pans ($F(1,508)=256.2$, $p<0.01$), and an interaction of the number of zooms and the number of pans ($F(2,508)=22.5$, $p=0.04$). This confirms our hypothesis that performance time is related to the amount of virtual navigation.

In order to better understand how performance is related to viewport size and task scale we present Figure 57. Figure 57 shows how participants saw different views of the data based on the semantic thresholds and viewport size. As explained earlier, the visualization was started at the beginning of each task as a "best fit" view for every column condition. In other words, the larger the viewport size, the more of the visualization could be seen at once, the deeper the zoom level presented at the beginning of the task, and consequently the more detail shown.

Figure 57 shows how the view of the visualization changed and at what points. For the one column condition only the house positions were shown initially. However, the houses were shown as small squares that were hard to see. Thereafter the houses became easier to see until the price of the house appeared after the six column condition.

Looking at Figure 57 and Figure 54 show two things: First, Figure 57 shows the performance times and how there is a drastic jump in performance when the visualization changes. Second, Figure 54 a linear decrease in the number of zooms performed for the same task. Putting the two together one can see that performance is based not only on the amount of zooms performed but also on the semantic thresholds. In other words, one could predict the performance times of a navigation task based on the starting position in space scale, the target position in space scale, *and* the semantic threshold zoom levels.

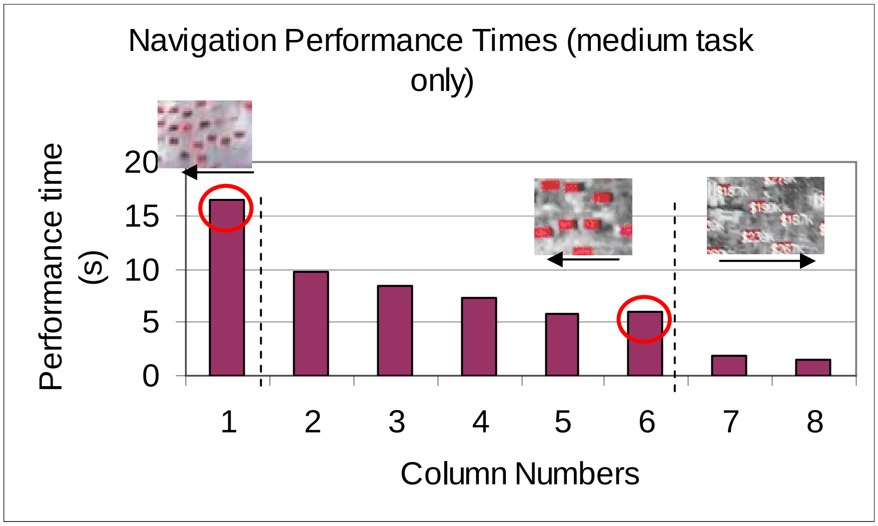


Figure 57. An illustration of what the geospatial visualization looked like for participants at different semantic thresholds.

9.4.2.2 Search Task Virtual Navigation Analysis

For the search task we performed similar analyses. First, we performed an ANOVA on understanding how the number of zooms performed correlated to the task scale and the column width. We found a main effect of task scale ($F(2,762)=270.0$, $p<0.01$), main effect of column width ($F(1,762)=114.1$, $p<0.01$), and an interaction of task scale and column width ($F(2,762)=16.5$, $p<0.01$).

Figure 58 shows a similar pattern as the navigation task: First, the higher the task scale of the task the less the participants zoomed in; the lower the task scale of the task the more participants zoomed in. Second, there is a general trend that the larger the viewport size the less participants needed to zoom in.

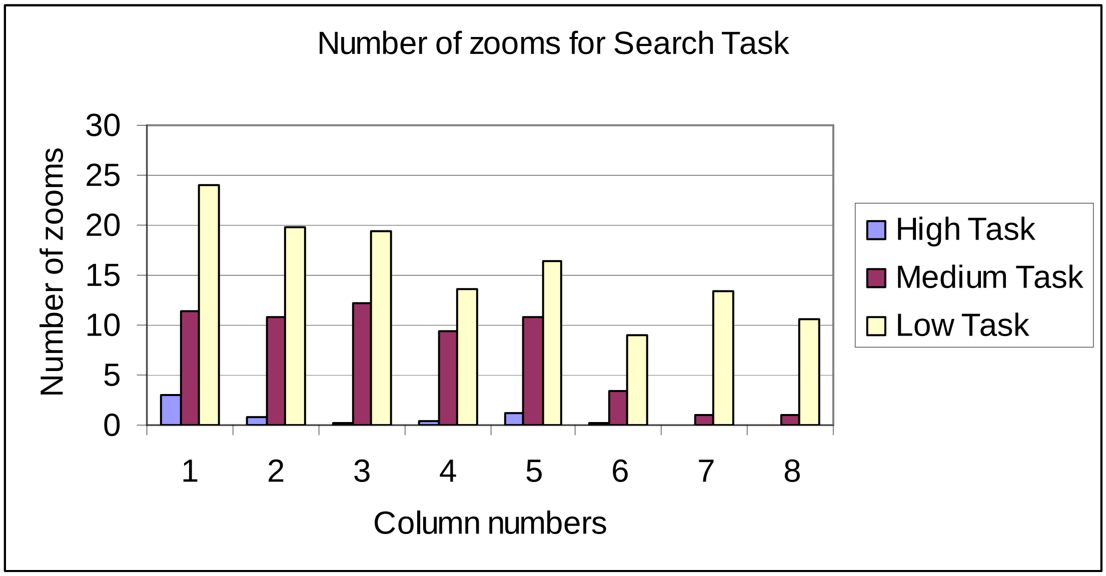


Figure 58. Average number of zooms for the search task.

Performing a similar ANOVA on virtual panning we found a main effect of task scale ($F(2,762)=23.9$, $p<0.01$), a main effect of column width ($F(1,762)=26.7$, $p<0.01$), and an interaction of task scale and column width ($F(2,762)=16.3$, $p<0.01$).

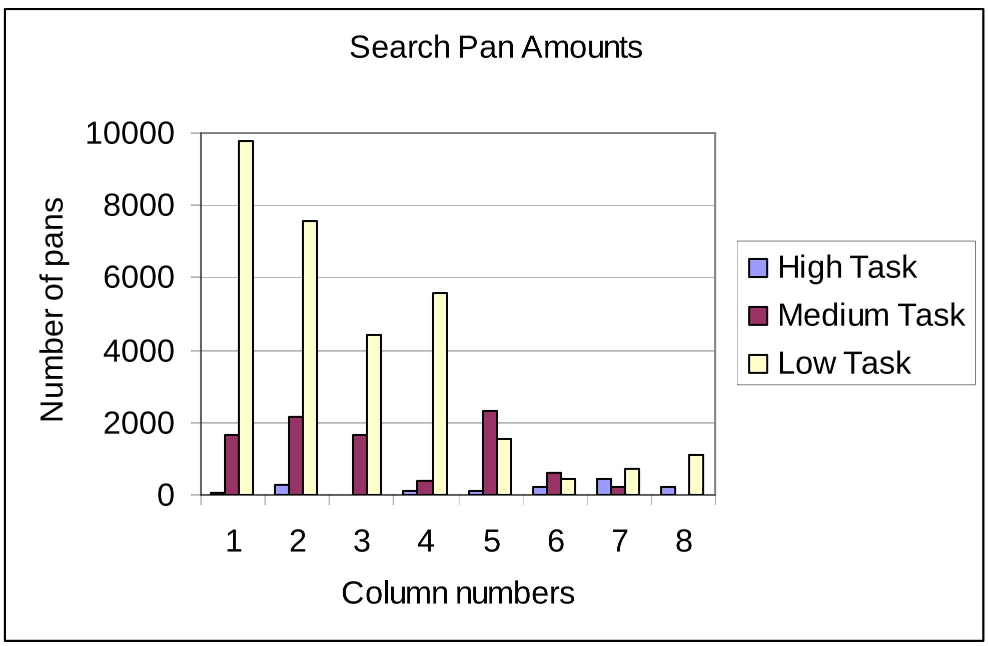


Figure 59. Average number of virtual pan amounts for the search task.

Figure 59 shows a more pronounced curve for the amount of panning in the search task than Figure 55 shows for the navigation task. This can be explained that more time was spent searching for a target which resulted in more panning. This is especially apparent for the low task (zoom level$_{0.8\text{-}1.0}$). Once again, the interaction between task scale and viewport size is apparent: the lower the task scale the more virtual navigation is required while at the same time the larger the viewport size the less virtual navigation is required.

Performing a similar ANOVA for lowest scale we found a main effect of task scale ($F(2,762)=479.6$, $p<0.01$), main effect of column width ($F(1,762)=264.0$, $p<0.01$), and an interaction of task scale and column width ($F(2,762)=258.4$, $p<0.01$). Figure 60 shows that the deeper the task scale the deeper participants were required to zoom in.

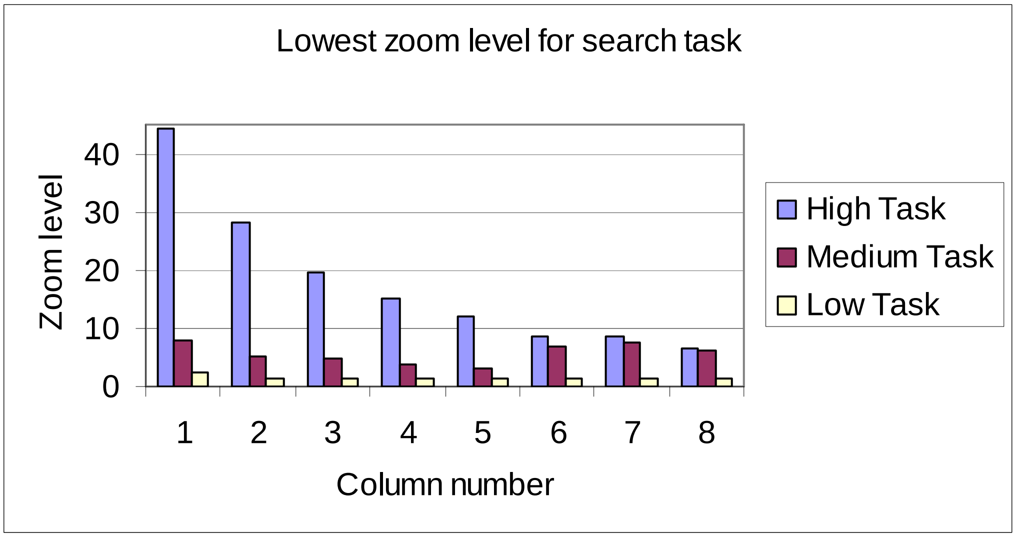


Figure 60. Average lowest zoom level for the search task. Note that the zoom level is not normalized between 0.0 and 1.0.

This additional required zooming for deeper task scales correlates to performance: Performing a similar ANOVA on performance time with the number of zooms and the number of pans as variables shows the same trend as before: a main effect of the number of zooms ($F(2,764)=376.0$, $p<0.01$), a main effect of number of pans ($F(1,764)=96.1$, $p<0.01$), and an interaction of the number of zooms and the number of pans ($F(2,37.5)=4.2$, $p=0.04$). Comparing the virtual navigation results from this subsection and the performance results in Figure 52, once again we can see how virtual navigation makes a large impact on performance times.

9.4.2.3 *Pattern Task Virtual Navigation Analysis*

We find a similar trend with the pattern data. Running an ANOVA for the number of zooms, we found a main effect of task scale ($F(2,90)=72.9$, $p<0.01$). Figure 61 shows the number of zooms for the three task scales.

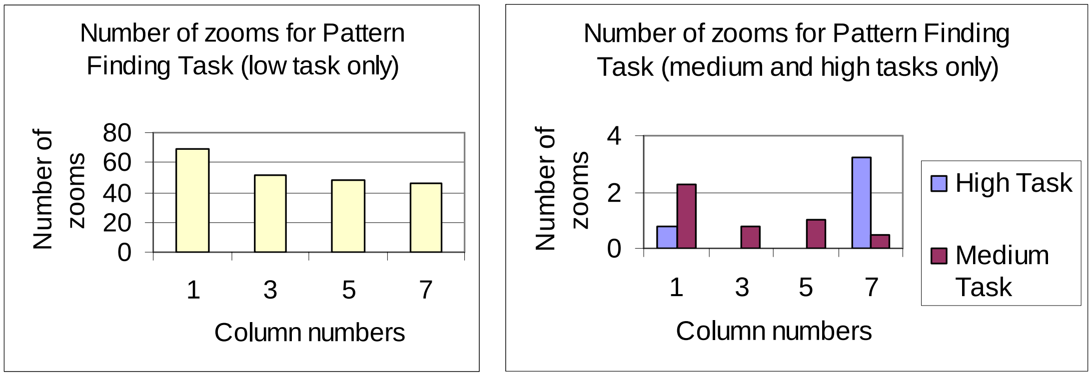


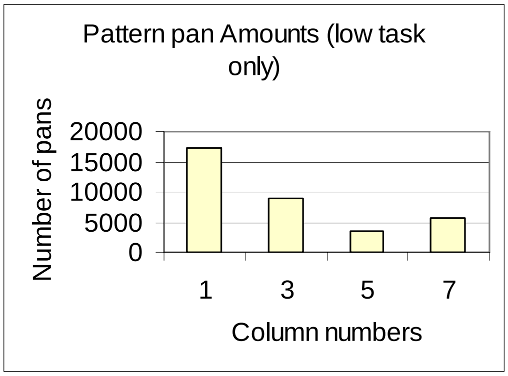
Figure 61. Average number of zooms for the pattern task.

The exception to the normal trend that we have seen is in the high task (zoom level$_{0.0\text{-}0.2}$) on the seven column condition where participants were observed to zoom out to better see the overall pattern. Previously participants were only observed to zoom in. However, as Figure 57 shows, the seven column condition started out seeing the geospatial position of the houses *and* the prices of the houses. As the task involved only finding the pattern of the geospatial positions of the houses, the text of the prices of the houses was a distraction. As a result, participants were observed to zoom out to go to a higher semantic view to more easily see *only* the geospatial pattern.

The implications of this finding are that more details are not always preferred. Semantic zooming was created for the very reason that too many details at once are confusing. Therefore, it is logical to conclude that understanding virtual navigation does not simply mean how much people might zoom in, but how much they might zoom out as well. This would be particularly important when doing multi-scale comparisons.

Running a similar ANOVA on virtual panning, we found a main effect of task scale ($F(2,90)=29.9$, $p<0.01$), a main effect of column width ($F(1,90)=7.8$, $p<0.01$), and an interaction of task scale and column width ($F(2,90)=7.6$, $p<0.01$).

Figure 62 shows the pan movement trends. The low task (zoom level$_{0.8\text{-}1.0}$) shows the same trend of pan amounts to performance times. That is, the amount of virtual pan movements decreases until the seven column condition. This is similar to how the performance time decreases until the seven column condition.



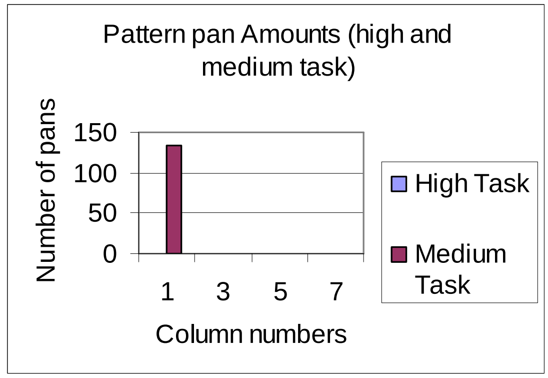


Figure 62. Average number of virtual pan movements for the pattern task. The high task (zoom level$_{0.0\text{-}0.2}$) did not have any recorded pan movements and the medium task (zoom level$_{0.2\text{-}0.4}$) only had recorded movements for the one column condition.

No virtual pan movements were detected for the high task (zoom level$_{0.0\text{-}0.2}$) and were only detected for the one column condition for the medium task (zoom level$_{0.2\text{-}0.4}$). This can be explained that participants did not need to pan to see the patterns at the overview levels.

Performing a similar ANOVA for lowest scale we found a main effect of task scale ($F(2,90)=49.2$, $p<0.01$), a main effect of column width ($F(1,90)=101.9$, $p<0.01$), and an interaction of task scale and column width ($F(2,90)=25.6$, $p<0.01$). Figure 63 the same trend in lowest zoom level as Figure 60 (from the search task) and Figure 56 (from the navigation task).

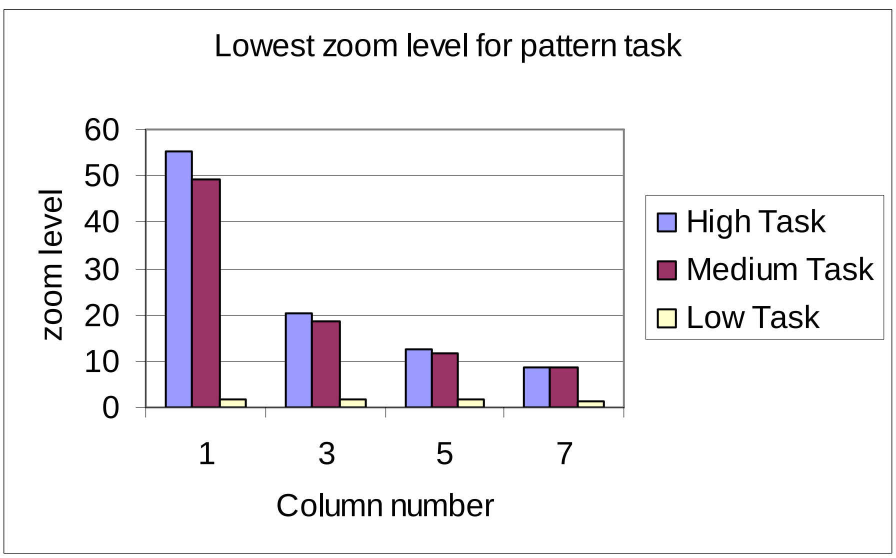


Figure 63. Average lowest zoom level for the pattern task. Note that the zoom level is not normalized between 0.0 and 1.0.

Performing a similar ANOVA on performance time with the number of zooms and the number of pans as variables shows the same trend as before: a main effect of the number of zooms ($F(2,92)=227.5$, $p<0.01$), a main effect of number of pans ($F(1,92)=23.8$, $p<0.01$), and an interaction of the number of zooms and the number of pans ($F(2,92)=4.2$, p=0.04). These results reinforce the idea that virtual navigation has a direct impact on performance for a variety of tasks.

Indeed, a linear regression of the same model as the ANOVA shows that the performance to number of zooms and number of pans has an R^2 of 0.858 and an adjusted R^2 of 0.853. This shows once again how strong a relationship the amount of virtual navigation has to performance.

9.4.2.4 Insight Task Virtual Navigation Analysis

The insight task was performed differently than the other tasks. First, it did not have specific task scales that we were testing for. Second, the reporting mechanism was different. Instead of having participants verbally speak their answer, participants wrote down their insights on paper. The rational was that more complete insights would be generated if written down than if spoken verbally. As a result of writing on paper, the participants were given a mobile stand to write their answers on.

However, the resulting performance statistics did not differentiate column widths; the only result was that participants on the one column condition did not have as many overview insights as the other column conditions.

Performing a one-way ANOVA with the number of zooms and as column width as the only variable we found non-significance. In addition, we did similar ANOVA's for the number of pans and the lowest zoom level and found non-significance between column widths. Performance metric to column width had already been performed (in the performance section – section 9.4).

9.4.2.5 Virtual Navigation Analysis Conclusions

There are a number of things that the virtual navigation analysis shows. First, semantic zooming is a key factor in understanding how much virtual navigation will be required for a particular task scale (see Figure 57). Knowing that particular tasks require a particular level of detail, the semantic zooming of the visualization dictates how much zooming in will be needed from a particular starting location. This starting location is dictated by the viewport size showing that the effects of semantic zooming are also influenced by viewport size.

The result is a series of linear step-wise performance curves. Specifically, it appears that there is a linear increase in performance within a semantic zoom threshold, but different linear performance curves between.

Second, we showed that performance times are directly related to virtual navigation, such as showing the results of a linear regression of the number of zooms and the number of pans correlated to performance resulted in an R^2 of 0.858 and an adjusted R^2 of 0.853.

The more virtual navigation required, the longer it takes to perform a task. This can be explained in a number of ways. The longer it takes someone to get to a particular target the longer it will take them to finish the task. The more zooming and panning involved the longer it takes to finish the task.

In addition, there appears to be similar pattern of performance time and the number of zooms. Visually comparing Figure 54 and Figure 57 validates the linear regression results that show there is a high correlation between virtual navigation and performance time.

So, the larger the viewport size, in general (with two exceptions), the less virtual navigation is performed. For example, with the number of zooms recorded for the low search task (zoom level$_{0.8\text{-}1.0}$), the number of zooms decreased 2.25 times from an average of 24 zooms for the one column condition to 10.6 zooms for the eight column condition.

The first exception was where people zoomed out to see fewer details for an overview (high) pattern task (zoom level$_{0.0\text{-}0.2}$) – from 0.8 average zooms on the one column condition to 3.3 average zooms on the eight column condition. This confirms the need for semantic zooming, that all details all the time are not always helpful.

The second exception is with the detailed (low) pattern task (zoom level$_{0.8\text{-}1.0}$) – 5591 average pans on the seven column condition compared to 3636 average pans for the five column condition. More panning was seen on the seven column condition (the largest column condition tested for that task) which appears to have influenced the performance time in a negative way.

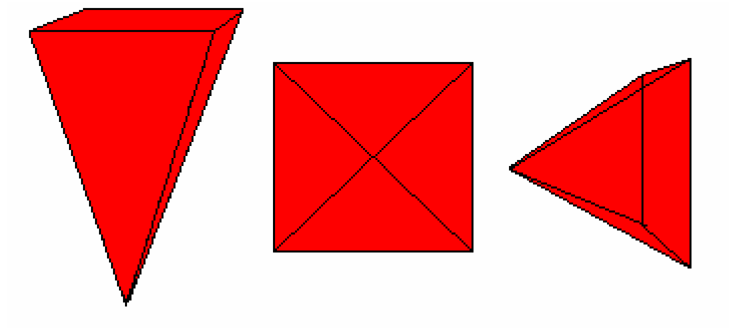
Third, as smaller viewports have to zoom in more to reach distant targets, they also have the disadvantage of more disorientation per zoom. Each time a person zooms in they have to reorient themselves with the new view. The smaller the viewport, the more difficult it is to reorient themselves thus taking increasing performance time (e.g. [51]).

9.4.2.6 Types of Virtual Navigation

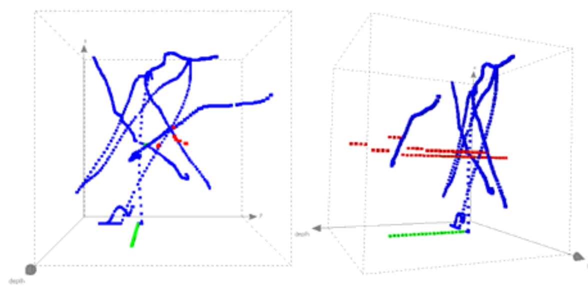
Not only did the virtual navigation of participants decrease as the viewport size increased, but the type of virtual navigation exhibited changed as well. Intuitively, if the physical navigation patterns of participants changed as the viewport size increased so too should the virtual navigation.

Figure 64 shows two different virtual navigation pattern visualizations; Figure 64.b is a visualization of virtual navigation from a participant performing a low pattern finding task on the one column condition; Figure 64.c is for a different participant for the same task using seven columns. The center images of Figure 64 are visualizations that are from the participant's point of view looking at the display and the right image is rotated to highlight the depth, or scale, that the participants zoomed - a side view.

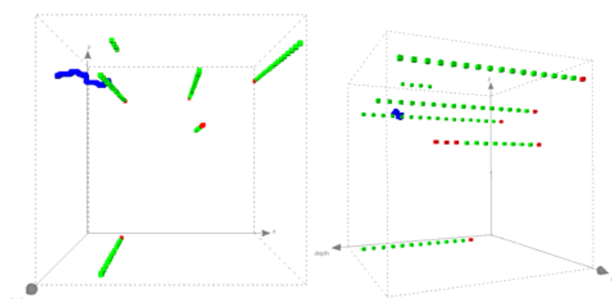
In other words, the left view is a view looking down at the geographic base and the right view is a view looking to the side of the geographic base. Figure 64.a shows three views of the space-scale diagram. The top, or aerial view (the middle image of Figure 64.a) corresponds with the left sides of Figure 64. The side view (the right image of Figure 64.a) corresponds with the right sides of Figure 64.



a)



b)



c)

Figure 64. Two visualizations of virtual navigation data for two different participants for the low pattern finding task. a) Virtual navigation data for a participant on the one column condition. b) Virtual navigation data for a participant on seven columns. The red dots represent zooming in, the green dots zooming out, and the blue dots represent panning.

The images in Figure 64 show a number of blue dots and lines. These blue dots and lines show where on the display the cursor was when actively panning. Active panning is actively moving the viewport while inactive panning (not visualized) is moving the cursor without moving the viewport. The red dots represent the participant zooming in and the green dots represent the participant zooming out.

As a note, the participant in Figure 64.b is seen to mostly zoom out while rarely zooming in. This is due to the participant's strategy of zooming back out at the same location thus occluding the zoom in points. The dots are not always seen to be connected as passive mouse movement (movement of moving the cursor's position, but not changing the underlying viewport) is not visualized.

Looking at the left image of Figure 64.a, one can see that the majority of the virtual navigation exhibited was panning. The right image shows that a large amount of zooming also took place at a few locations.

On the other hand, on the left image of Figure 64.b one can see that only a little panning was exhibited and that all other virtual navigation was exhibited as "zooming columns." The zooming columns show that the participant was interested in particular points and would zoom into the point, most likely perform physical panning around the point of interest, then zoom back out.

Not only is the amount of panning different between the two images, but the amount of zooming. One may notice that for Figure 64.a the zooming columns were larger than the zooming columns in Figure 64.b. The participant on the seven column condition (Figure 64.b) would zoom in and zoom out and perform little panning. However, the zoom in/out points for the zooming columns were fewer than the zoom columns in Figure 64.a. In other words, the participant using the seven columns (Figure 64.b) zoomed in/out often but for each zoom column he zoomed in/out less than the participant on the one column (Figure 64.a).

One can see that the virtual navigation for the larger viewport size is almost entirely limited to virtual zooming. Almost all panning was performed physically. Corresponding physical navigation visualizations (see Figure 85) show that participants performed a larger degree of physical panning to compensate for lack of virtual panning.

The visualizations of virtual navigation shown are representative of the virtual navigation exhibited for their corresponding viewport sizes for all participants. Although every participant had a unique virtual navigation pattern, overall their characteristics were similar based on what viewport size was used and task was performed.

9.4.3 Physical Navigation Analysis

This subsection analyzes the physical navigation of the participants. First, we will analyze head rotation of the participants then analyze the physical 3-dimensional position (x,y,z position).

9.4.3.1 Head rotation

A normal healthy person has head rotation along three axes: x, y, and z. As a person's head exists along these axes it can also rotate along the axes if the origin of the axes is thought to be at center of the head. Yaw is the side to side motion of the head (e.g. looking left or right). This might be performed when a participant wants to look from side of the display to another.

Pitch is the up and down, or forward and backward, movement of the head. A participant might perform a pitch movement when trying to look from the top to the bottom of the display.

A roll movement of the head is tilting the head closer to one shoulder and farther away from the other. In general this kind of movement does not benefit participants in looking at a display in the experiment and will not be analyzed.

Performing a 2-way ANOVA for all the head pitch data (forward and backward) with task type and column width as variables resulted in non-significance. However, running a similar ANOVA but for head yaw (side to side) found a main effect of column width ($F(1,1400)=4.6$, $p<0.01$), a main effect of task type ($F(3,1400)=1.67$, $p<0.01$), and an interaction of column width and task type ($F(3,1400)=3.7$, $p=0.01$). Post-hoc analysis shows that the navigation task was in a different group from pattern and search (the insight task was in both groups).

In other words, we did not find that pitch (looking up and down) was statistically significant, but we did find that yaw (looking side to side) was. The yaw results are intuitive in the one would expect a general increase in side to side motion for larger viewport sizes and harder (deeper scale) tasks.

The rest of this section explains head rotation analysis per task.

9.4.3.1.1 Navigation Task Head Rotation Analysis

For the navigation task we ran a two-way ANOVA for head pitch movement with task scale and column width as variables. We found a main effect of task scale ($F(1,508)=4.84$, $p = 0.028$) showing that the two task scales had different amounts of head pitch. Figure 65 shows the average amount of head rotation differences. So, for any given 1/30th of a second, the average head rotation distance from the previous known location (in degrees) is shown.

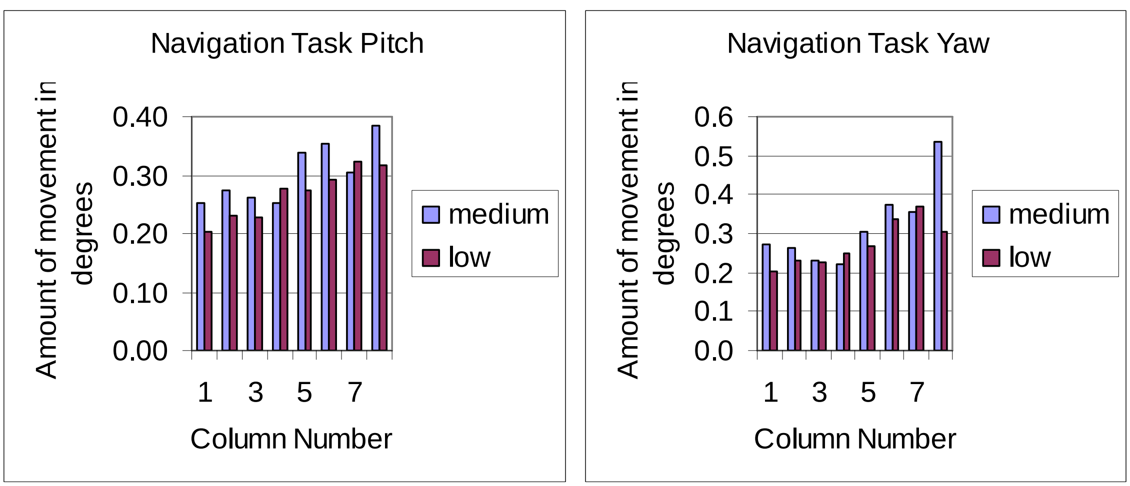


Figure 65. Average amounts of head pitch movement (left) and average amounts of head yaw movement (right) for the navigation task.

Performing a similar ANOVA for head yaw movement, we found a main effect of task scale ($F(1,508)=8.39$, $P < 0.01$) showing the same trend as the head pitch movement that the different task scale resulting in different head yaw movements (see Figure 65).

9.4.3.1.2 Search Task Head Rotation Analysis

Similar ANOVA tests found the same trend as the navigation task: Head pitch movement resulted in a main effect of task scale ($F(2,762)=71.08$, $p < 0.01$) and head yaw movement resulted in a main effect of task scale (ss $F(2,762)=74.46$, $p < 0.01$) (see Figure 66). Post-hoc Tukey HSD analysis showed that the high task was in a different group than the medium and low task for both ANOVA's.

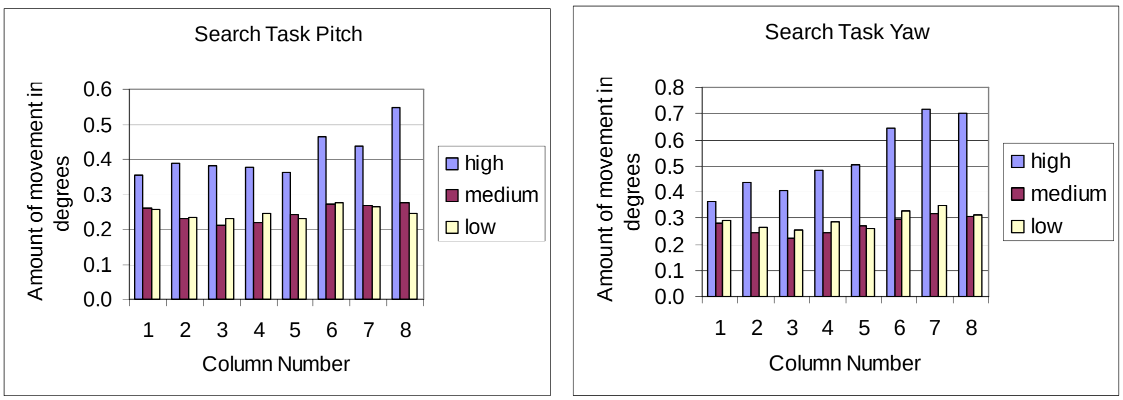


Figure 66. Average amounts of head pitch movement (left) and average amounts of head yaw movement (right) for the search task.

9.4.3.1.3 Pattern Task Head Rotation Analysis

Similar ANOVA tests found a different trend: Head pitch movement resulted in a main effect of column width ($F(1,90)=1.24$, $p=0.05$), and head yaw movement resulted in a main effect of column width ($F(1,90)=20.37$, $p < 0.01$) (see Figure 67).

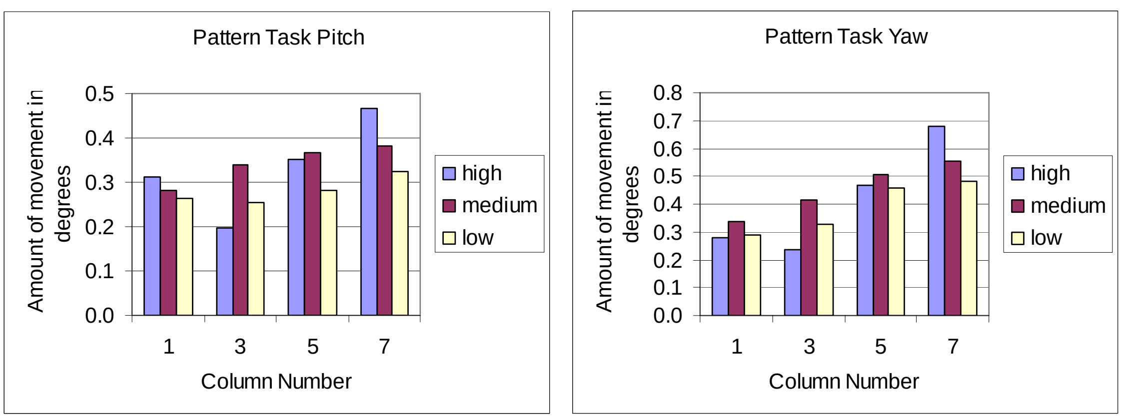


Figure 67. Average amounts of head pitch movement (left) and average amounts of head yaw movement (right) for the pattern task.

This increased yaw head movement over the previous tasks is intuitive as there are more comparisons being performed. Where the other tasks were looking for only a single target, the pattern task was looking for an overall trend for a particular task scale. This translated into looking at all the targets which made better use of the overall display.

9.4.3.1.4 Insight Task Head Rotation Analysis

One-way ANOVA tests were performed on the insight task data as well with column being the only variable (the insight task did not have different task scales). However, non-significance resulted for both the head pitch and head yaw data. This is similar to the navigation and search task that did not have column width as a significant variable.

9.4.3.2 Head Gaze Analysis

In addition to analyzing physical head rotation movement, we performed analyses of where participants were looking. As we knew where the display was, what the display dimensions were, what the participant's physical location was at any particular time, and what their head rotation was, we can accurately estimate where on the display the participants head gaze was. According to research on head gaze analysis, head gaze can be attributed to between 87-89% accuracy of eye gaze direction [98].

In order to project the vector (or head gaze) of a participant we need to transform a vector from one reference from to another. In other words, as the participants' head uses one set of axes and the display uses another, we need to transform the vectors (i.e. yaw, pitch, roll) to understand how they translate to the other set of axes (the display) [45]. We used Eulerian rotations to do this. The Eulerian rotations involve repetition of rotations about one particular axis: *XYX*, *XZX*, *YXY*, *YZY*, *ZXZ*, *ZYZ*.

However, as the x-axis is the axis that designates the participants' head gaze, we can simply use a modified version of the Euler rotation matrix (see Figure 68) with the participants' head rotation data. To find where the head gaze of a person intercepts the display is simply finding where the vector (i.e. the head gaze) intercepts the plane (i.e. the display).

$$\begin{bmatrix} 0 & \sin(y)\sin(z)\cos(x)+\cos(y)\sin(x) & 0 \\ 0 & -\sin(y)\sin(z)\sin(x)+\cos(y)\cos(x) & 0 \\ 0 & -\sin(y)\cos(z) & 0 \end{bmatrix}$$

Figure 68. Modified Euler rotation matrix used to get an accurate head gaze vector. The unmodified matrix does not have zeroes in the first and last columns.

After every physical navigation data point was computed to create the appropriate head gaze position we ran a modified Douglas-Peucker algorithm [37] to track the gaze distance. The Douglas-Peucker algorithm is a well-known cartographic algorithm for automatically generating digital maps at different scales. By having different thresholds of distances for different scales of digital maps can be produce maps that have different amounts of jagged lines. For instance, a small threshold might produce a map with very jagged shores, closer to the actual shore. However, at larger thresholds the shores becomes more defined with less jaggedness.

The modified Douglas-Peucker algorithm that we created takes the same concept but uses physical distances of the participants instead of shore lines. Precisely, the algorithm takes the current pixel that a participant is looking at (in the data), then calculates the distance from the last pixel that they were looking at. The algorithm then checks for two things. First, it takes out distances that are obviously too far apart for a person to be able to look at in 1/30th of a second. Second, it ignores jitter of the head. That is, it ignores small movements of less than 10 pixels. The algorithm adds up all distances that meet the two criteria.

The conclusion of the algorithm is that the resulting stats and graphs show the results of all the head movements of the participants that were not jitter. The VICON system that we used was very precise and recorded all physical positioning every 1/30th of a second. We define jitter as the small movements of the head that a person performs to keep his head straight but are not used for looking at different parts of the display.

We then performed a two-way ANOVA comparing the resulting total distance with task type and column width as variables. We found a main effect of task type ($F(3,48)=34.6$, $p<0.01$), and a main effect of column width ($F(1,48)=5.3$, $p=0.024$). Post-hoc analysis of the task types shows that the insight task was in a different group than all the other tasks.

The rest of this section describes head gaze per task. Note that the "total gaze distance" for a particular task is the total area in terms of pixels that participants gazed at. So, a gaze distance of 200 pixels would be a sum of the different

9.4.3.2.1 Navigation Task Head Gaze Analysis

We performed a two-way ANOVA for total distance with task scale and column width as variables for only the navigation task. We found a main effect of task scale ($F(2,46)=14.4$, $p < 0.01$), and an interaction of task scale and column width ($F(1,12)=4.2$, $p = 0.06$). With the exception of the outlier at the six column condition there also appears to be a trend of column width for the medium task as well (zoom $\text{level}_{0.2\text{-}0.4}$) (see Figure 69). The reader may recall that the reason the six column condition is an outlier is due to the target being located on a bezel.

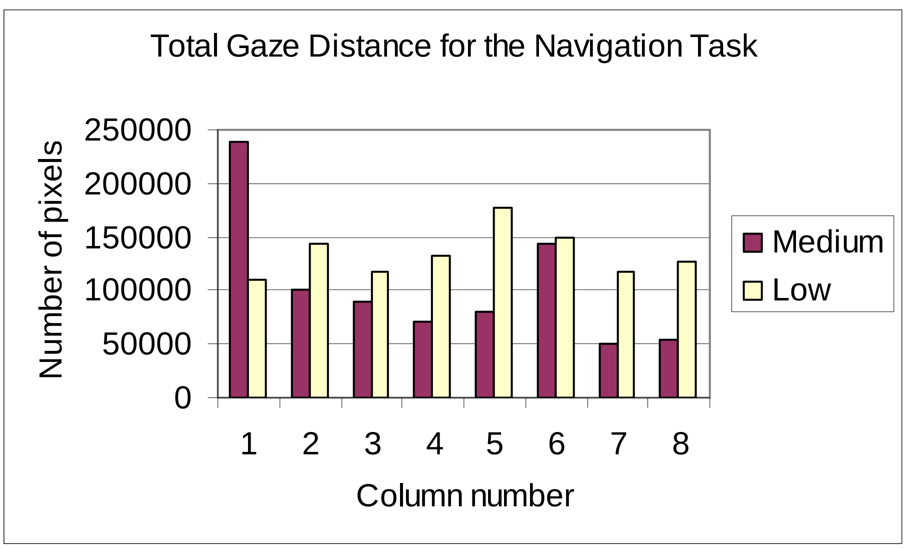


Figure 69. Average distance in pixels that participants looked at for the navigation task.

9.4.3.2.2 Search Task Head Gaze Analysis

Performing a similar ANOVA but with the search task found a main effect of task scale ($F(2,18)=31.26$, $p < 0.01$). Post-hoc Tukey HSD analysis shows that the low task (zoom level$_{0.8\text{-}1.0}$) is different from the medium (zoom level$_{0.2\text{-}0.4}$) and high (zoom level$_{0.0\text{-}0.2}$) tasks. Similar to the navigation task, the different task scales clearly have different head gaze requirements. As such, there is a different total amount of head gaze distance (see Figure 70).

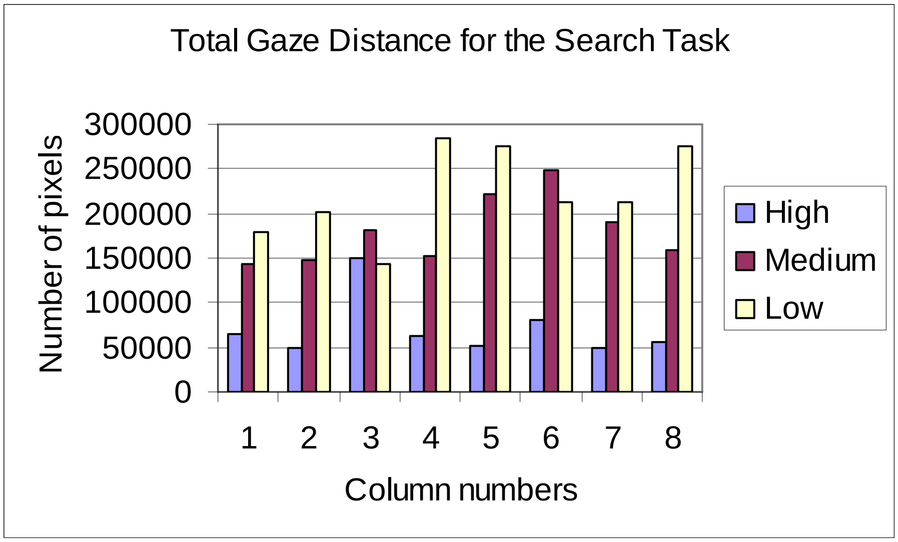


Figure 70. Average distance in pixels that participants looked at for the search task.

9.4.3.2.3 Pattern Task Head Gaze Analysis

Performing a similar ANOVA but with the pattern task found a main effect of task scale ($F(2,6)=9.07$, $p=0.014$), a main effect of column width ($F(1,6)=8.87$, $p=0.025$), and an interaction of task scale and column width ($F(2,6)=5.17$, $p = 0.049$). Post-hoc Tukey HSD analysis showed that the low task (zoom level$_{0.8\text{-}1.0}$) is different from the medium (zoom level$_{0.2\text{-}0.4}$) and high (zoom level$_{0.0\text{-}0.2}$) tasks.

The trend exhibited in Figure 71 shows that this task is different from the navigation and search tasks. At this point it should become increasingly obvious to the reader that both physical and virtual navigation behaviors are different for different tasks and task scales.

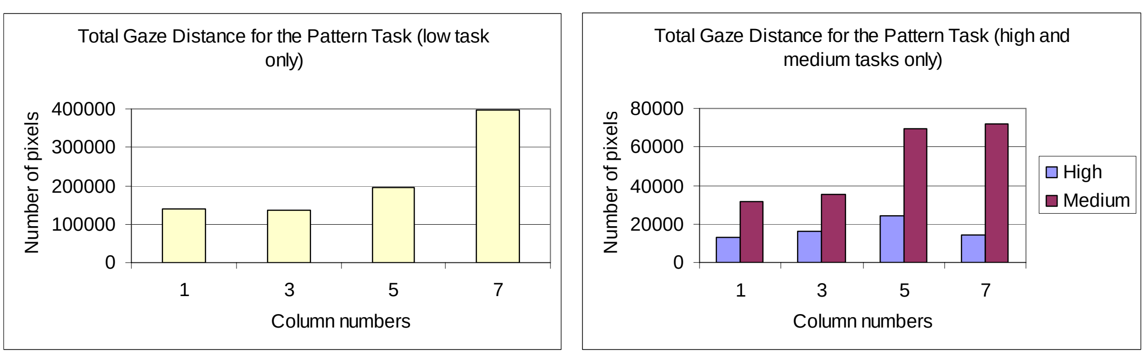


Figure 71. Average distance in pixels that participants looked at for the search task.

In addition, one can see that between the additional head gaze and the additional virtual panning (see Figure 62) why the performance time for the seven column condition is greater than the five column condition.

9.4.3.2.4 Insight Task Head Gaze Analysis

We performed a one-way ANOVA for the insight task for the total head gaze distance with column width as the variable. We found a main effect of column width ($F(1,2)=50.25$, $p = 0.02$) (see Figure 72). Similar to the pattern task we found that for this complex task (as opposed to navigation and search tasks) that there is a trend of more total gaze distance as the viewport size increases.

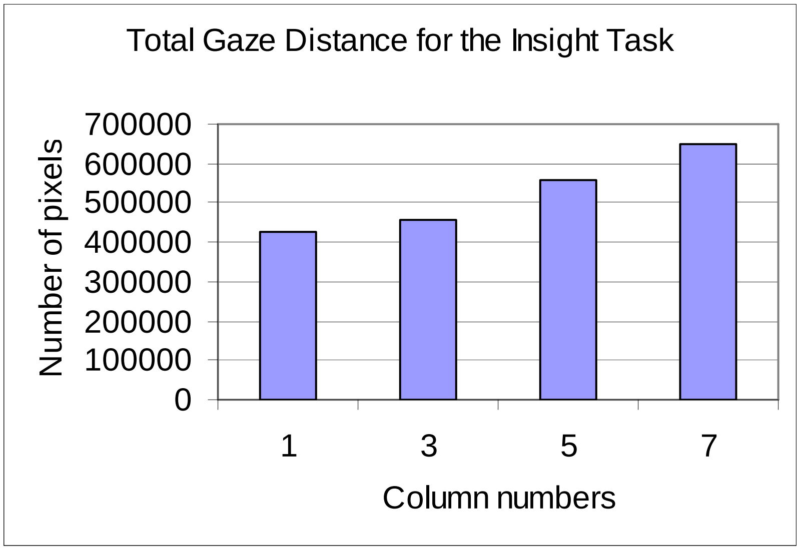


Figure 72. Average distance in pixels that participants looked at for the search task.

9.4.3.3 Head Rotation and Head Gaze Conclusions

The head rotation and head gaze analyses showed a number of things. First, they showed that different head movement behaviors were exhibited at different task scales. This is intuitive as different task scales require different amounts of effort from participants.

For example, the high pattern task (zoom $\text{level}_{0.0\text{-}0.2}$) shows only a 0.93 (93%) increase of average head gazes from 13,315 gazes for the one column condition to an average of 14,268 gazes for the seven column condition. In contrast, the low pattern task (zoom $\text{level}_{0.8\text{-}1.0}$) shows a 2.86 (286%) increase of average head gazes from an average of 138,868 gazes for the one column condition to an average of 397,802 gazes for the seven column condition.

Also, different tasks exhibit different behaviors as well. For example, a navigation task is different from a pattern task in a number of ways. One way is that a navigation task is a task where one must simply navigate, or go to, the target. However, a pattern task relies on more perceptual cues as it includes many more targets. Second, the pattern task contains a number of comparisons of targets for the person to get a general idea of the data.

With these additional comparisons, additional viewport size can better used. In other words, the complex tasks (pattern and insight tasks) had a lot more of looking back and forth. This makes even more sense when the virtual navigation part is compared (section 9.4.2). It is intuitive to presume that a certain amount of data must be seen for the task to be finished. If less virtual navigation is performed then it is intuitive that more physical navigation must make up for it. For example, the additional comparisons in the pattern task are shown either in additional virtual navigation or additional physical navigation; regardless of which form of navigation is used, they must be performed to complete the task.

To better understand how physical navigation and virtual navigation have a relationship with performance we performed a linear regression of performance to the number of zooms, the head gaze total distances, and the number of zooms crossed by the head gaze total distances. The resulting R^2 is 0.878 and the adjusted R^2 is 0.871. This shows that there is a strong relationship with virtual and physical navigation in predicting performance.

Careful analysis of corresponding virtual and physical navigation charts shows an inverse relationship. It appears that as virtual navigation increases physical navigation subsequently decreases and vice versa. This leads to the idea that a certain amount of navigation must be performed to complete the tasks. It does appear to matter whether the navigation is virtual or physical to be *able* to complete the task. However, it does matter in the performance time of the task.

9.4.3.4 Physical Bodily Movement

In order to complete the analysis of data from the capstone experiment we analyzed the physical distances of the participants in 3-dimension space. Where we have shown the results of analyses from head rotation and head gaze data, we now present movement of the participants' body.

We analyzed participants' physical bodily movement in three ways: Range of movement, standard deviation of physical position, and total physical distance. Range of movement is the actual range of physical area usage. This was measured by taking the maximum position and subtracting the minimum position. For example, taking the maximum position along the X-axis (maxX) and subtracting it from the minimum position along the X-axis (minX): maxX – minX.

The standard deviation of physical position was generated using normal standard deviation techniques using all the recorded participants' physical positions. The standard deviation of physical position was used to understand how much people preferred to stay in one area. It answers the question of how much movement around a central location took place.

Physical distance was calculated the same way total head gaze distance was calculated by using a modified Douglas-Peucker algorithm. By using the algorithm we guaranteed that what we were analyzing was actual movement from one physical location to another and not jitter of people standing at one location.

Figure 73 shows an illustration of how the three axes map to the large display. The illustration is a simulated top shot of looking at the display from above. The brown line forms the back of the display stand while each semi-circle represents the back of each of the individual column stands.

Figure 73. Illustration of the x, y, and z axes with relation to display.

The X-axis runs parallel to the display; a participant moving along the X-axis moves beside the display. The Y-axis runs perpendicular to the display; a participant moves along the Y-axis moves closer to or further away from the display. The Z-axis is the third dimension of the display, running along the height of the display; a participant moving along the Z-axis is getting closer to the floor (e.g. crouching) or getting closer to the ceiling (e.g. standing up).

9.4.3.4.1 Navigation Task Bodily Movement Analysis

To better understand the navigation task we performed a two-way ANOVA for the X range of position (i.e. movement parallel to the display) with task scale and column width as variables. We found a main effect of column width ($F(1,508) = 78.35$, $p<0.01$). Performing a similar ANOVA for Y range of movement (i.e. movement to and from the display) found a main effect of column width ($F(1,508) = 8.29$, $p < 0.01$).

Figure 74 shows the trends that as the viewport size increases the range of X position increases as well. However, an opposite effect is seen with the Y position. An obvious outlier to the trend in the X position data is for the seven column condition. The outlier is due to the navigation targets being placed randomly; it so happens that the target for the seven column condition was randomly placed almost exactly in front of the starting position of the participants. As a result little movement parallel to the display was needed.

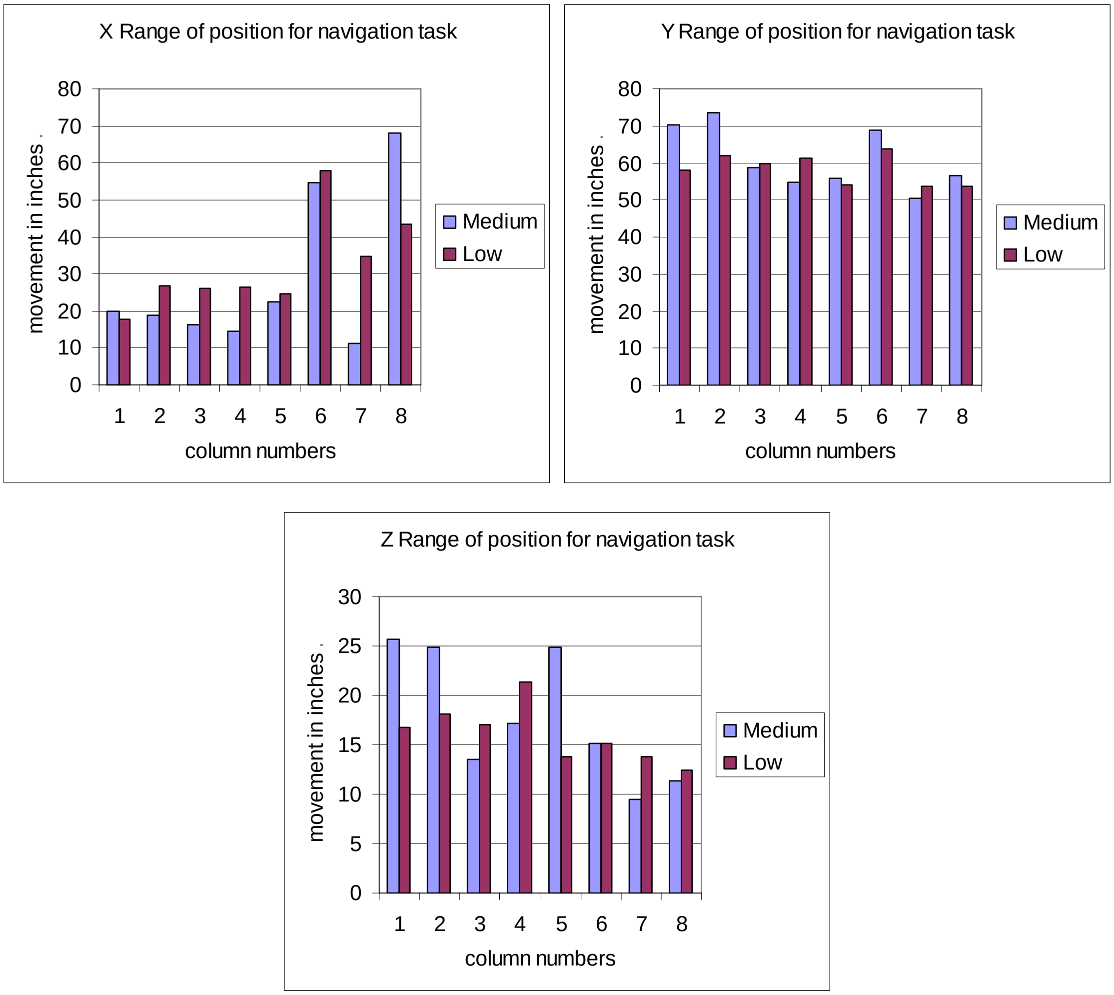


Figure 74. Average amount of range of movement in the X, Y, and Z axes for the navigation task.

Performing a similar ANOVA for the Z range of movement found a main effect of column width ($F(1,508)=28.3$, $p<0.01$) and an interaction of task scale and column width ($F(1,508)=5.26$, $p=0.02$).

Figure 74 shows the general trend that as the viewport size increases participants crouched less. This is intuitive in that the larger viewports allowed a greater width to perform the navigation task so that crouching, which is more uncomfortable, was performed less.

Performing a similar ANOVA on the standard deviation of the X-axis physical positions found a main effect of task scale ($F(1,508)=70.6$, $p<0.01$), a main effect of column width ($F(1,508)=123.28$, $p<0.01$), and an interaction of task scale and column width ($F(1,508)=62.6$, $p<0.01$). Performing an ANOVA on the standard deviation of the Y physical positions found a main effect task scale ($F(1,508)=31.3$, $p<0.01$) and an interaction of task scale and column width ($F(1,508)=13.1$, $p<0.01$). The ANOVA on the standard deviation of the Z physical positions found a main effect of task scale ($F(1,508)=91.7$, $p<0.01$), a main effect of column width ($F(1,508)=116.9$, $p<0.01$), and an interaction of task scale and column width ($F(1,508)=88.9$, $p<0.01$).

Figure 75 shows how the larger the viewport size the greater the variation in physical position. In other words, the larger the viewport size the greater the differences in bodily position of the participants; the larger the viewport size the more the participants' positions deviated from each other.

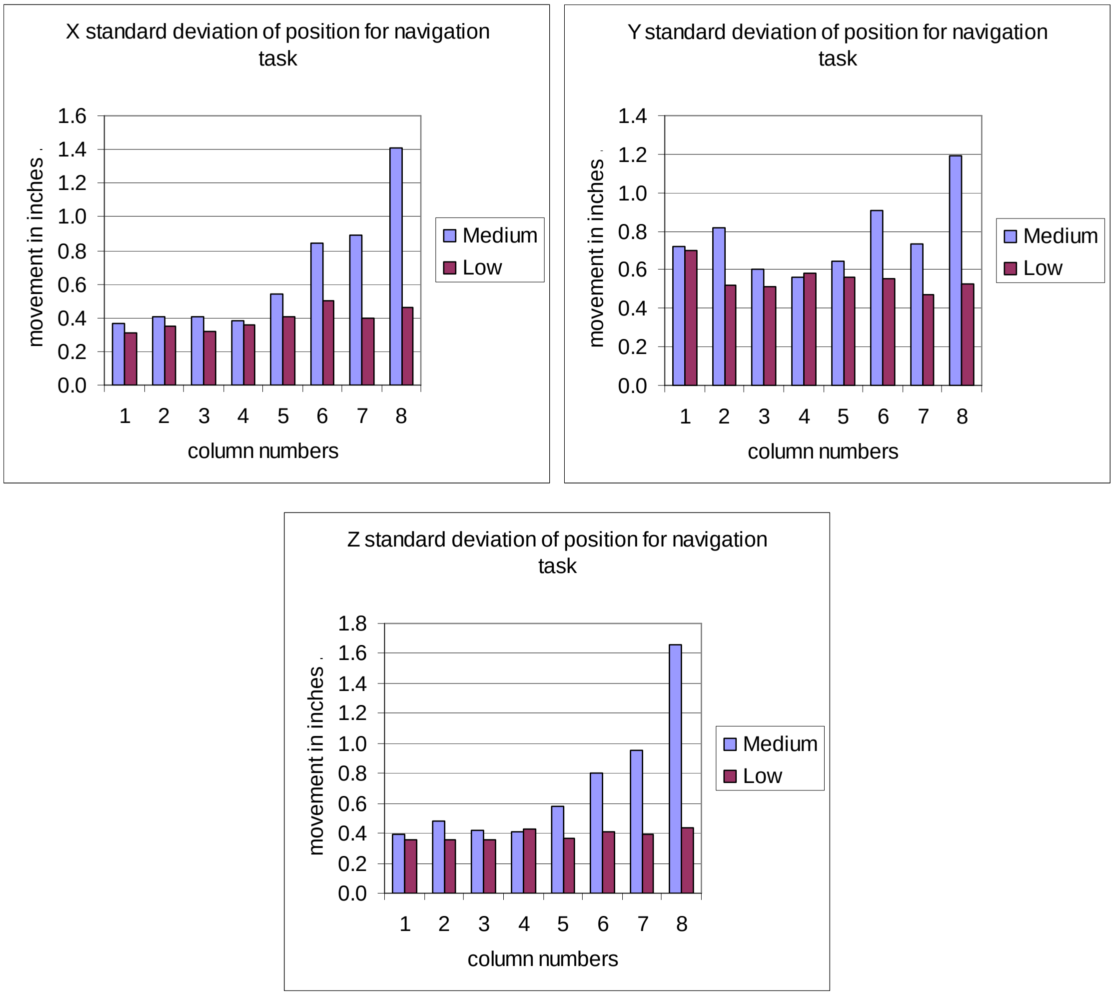


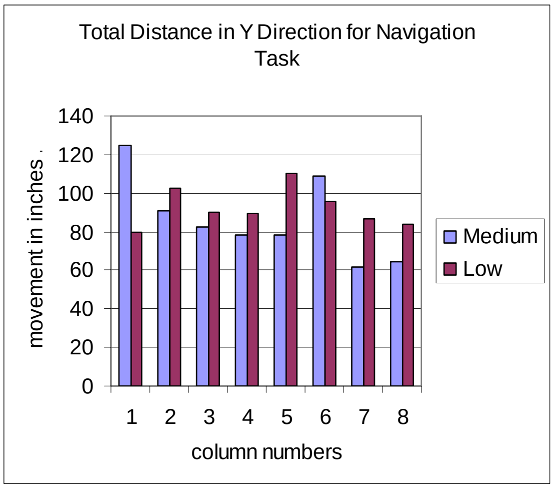
Figure 75. Average standard deviations of position in the X, Y, and Z axes for the navigation task.

In other words, the amount of physical position in the same places that participants had to conform to had greater variance the larger the display. Referring back to Figure 47, one can see that the larger the display the more possible physical positions a participant might take.

In addition, there is an increase variation towards the end of the curve. This can be accounted for by the fact that people could be in a greater variance of positions to still complete the task as the task was performed entirely by physical navigation. For instance, taller participants and shorter participants did not have to converge on the same positions as they could easily see the target from their perspective heights.

Performing ANOVA's on the total distance of the navigation task and the X total distance resulted in non-significance. However, performing an ANOVA on Y total distance found a main effect of column width (F(1,508)=5.8, p=0.016). Also, performing an ANOVA on Z total distance found a main effect of column width (F(1,508)=8.75, p<0.01) and an interaction of task scale and column width (F(1,508)=3.79, p=0.05).

In other words, Figure 76 shows the larger the viewport size the less participants got closer to the display and the less they crouched down. It is intuitive that the larger the display the less participants needed to come close to the display or crouch down to make effective use of the display.



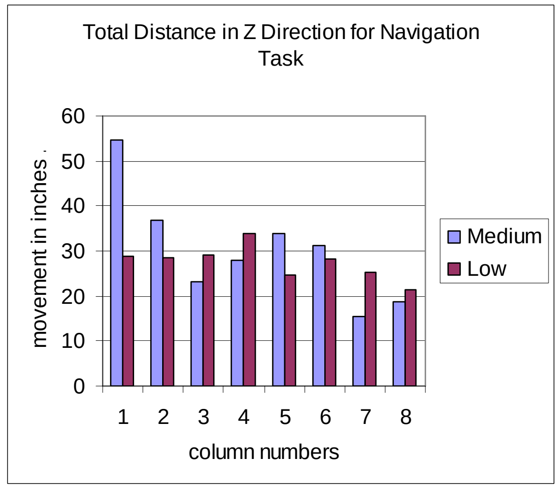


Figure 76. Average total distance of participants in the Y and X axes for the navigation task.

9.4.3.4.2 Search Task Bodily Movement Analysis

We performed similar analysis with the search task. For the X range of position ANOVA we found a main effect of task scale (F(2,762)=27.18, p<0.01), a main effect of column width (F(1,762) =82.3, p<0.01), and an interaction of task scale and column width (F(2,762)=3.31, p=0.036). The ANOVA for the Y range of position found a main effect of column width (F(1,762)=14.68, p <0.01) and a main effect of task scale (F(2,762)=76.35, p<0.01). The ANOVA for the Z range of position found a main effect of task scale (F(2,762)=29.6, p<0.01) and a main effect of column width (F(1,762)=12.38, p<0.01).

Figure 77 concurs with Figure 74 (navigation task counterpart) that shows that there appears to be a trend that as the viewport size increases the range of motion in the X-axis increases while decreases for the Y and Z axes. The reader may recall that the capstone experiment added a greater viewport width and held the height constant. Interestingly, as more width was added the participants used more of it to their advantage. However, as participants used more display width they used less of the height (i.e. Z-axis) and stood back farther (Y-axis).

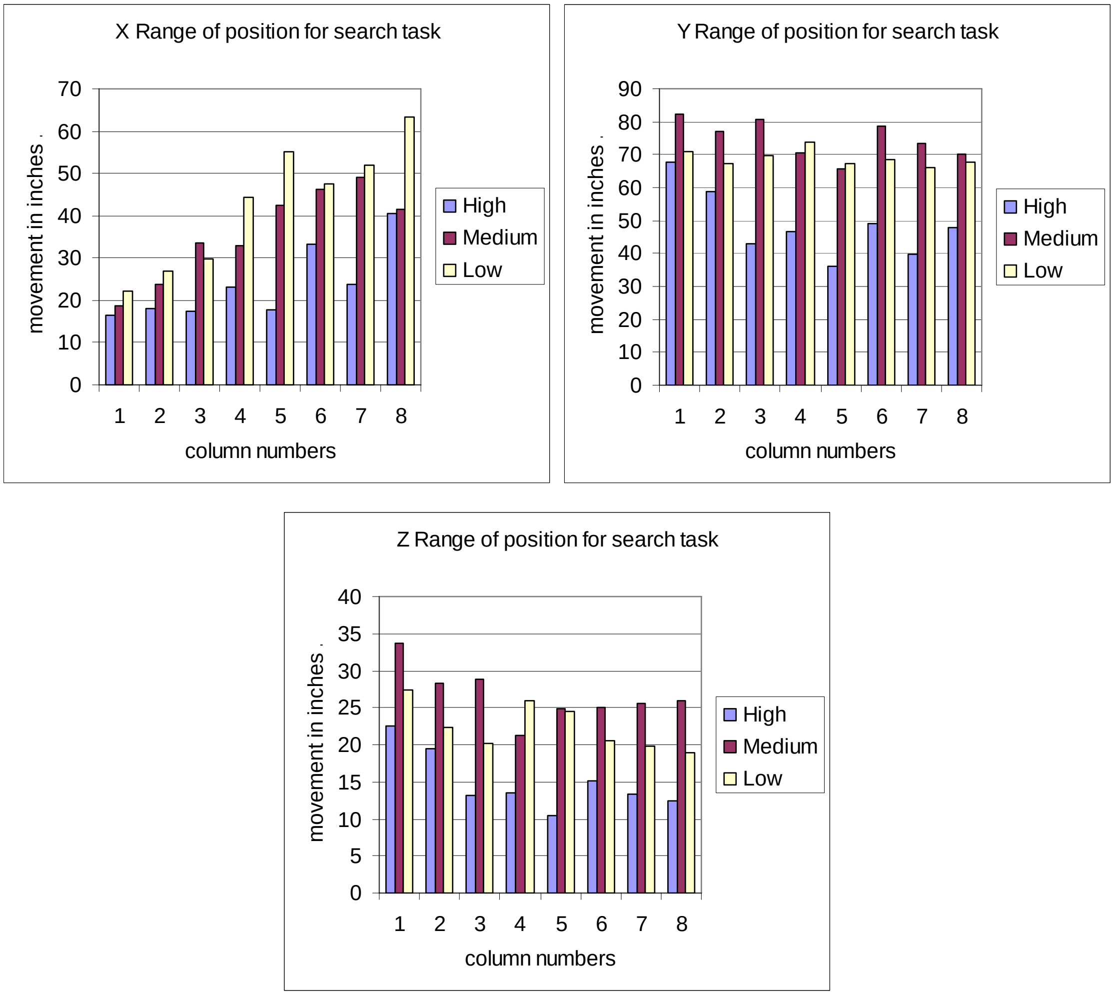


Figure 77. Average amount of range of movement in the X, Y, and Z axes for the search task.

In addition, there appears to be a trend of task scale to range of movement as well. As the tasks decreased in scale (deeper scales) then participants used more physical navigation for all of three axes (i.e. X, Y, and Z axes). Looking back at section 9.4.2 (the virtual navigation section), one can see that this leads to conclusions that as the tasks become more difficult (deeper scales) that more navigation is performed – both virtual and physical.

Performing a similar ANOVA on the X standard deviation of position found a main effect of task scale ($F(2,762)=80.81$, $p<0.01$). The ANOVA for the Y standard deviation of position found a main effect of task scale ($F(F,762)=21.09$) and a main effect of column width ($F(1,762)=6.1$, $p=0.013$). The ANOVA for the Z standard deviation found a main effect of task scale ($F(2,762)=94.8$, $p<0.01$).

Figure 78 shows that as task scales deepen and take more effort that there is also less variation in the positioning of the participants. In other words, the harder the task, the more likely a person is to be at similar positions as other participants. For example, the high task (zoom $level_{0.0\text{-}0.2}$) shows the greatest variation in positions than the other tasks.

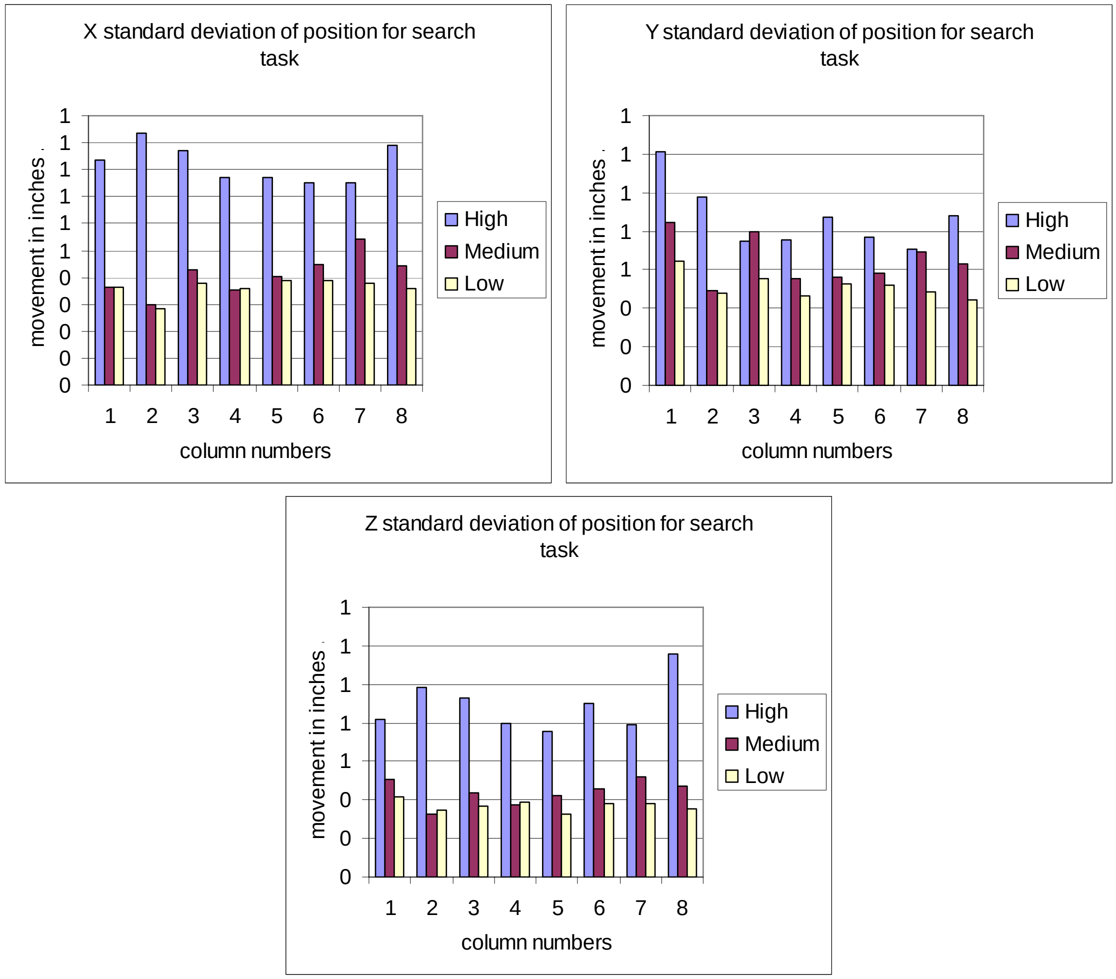


Figure 78. Average standard deviations of position in the X, Y, and Z axes for the search task.

Performing a similar ANOVA for the total distance for the search task found a main effect of task scale ($F(2,762)=31.6$, $p<0.01$). Similarly, the ANOVA for the X total distance resulted in a main effect of task scale ($F(2,762)=24.7$, $p<0.01$), and a main effect of column width ($F(1,762)=4.52$, $p=0.03$). The ANOVA for the Y total distance resulted in a main effect of task scale ($F(2,762)=35.6$, $p<0.01$). The ANOVA for the Z total distance resulted in a main effect of task scale ($F(2,762)=23.29$, $P<0.01$).

In general, Figure 79 shows two things. First, it shows that as viewport size increases participants takes advantage of it and use the additional size.

Second, the amount of total physical navigation is different for different task scales. The reader should *not* understand that there naturally is a greater total physical distance because of longer tasks. As the deeper task scales increased the tasks took longer amounts of time to complete. However, this does not necessarily explain larger distances. Participants could have chosen not to move from a particular position and to only virtually navigate. However, this was not the case showing that people prefer to move around when given the opportunity.

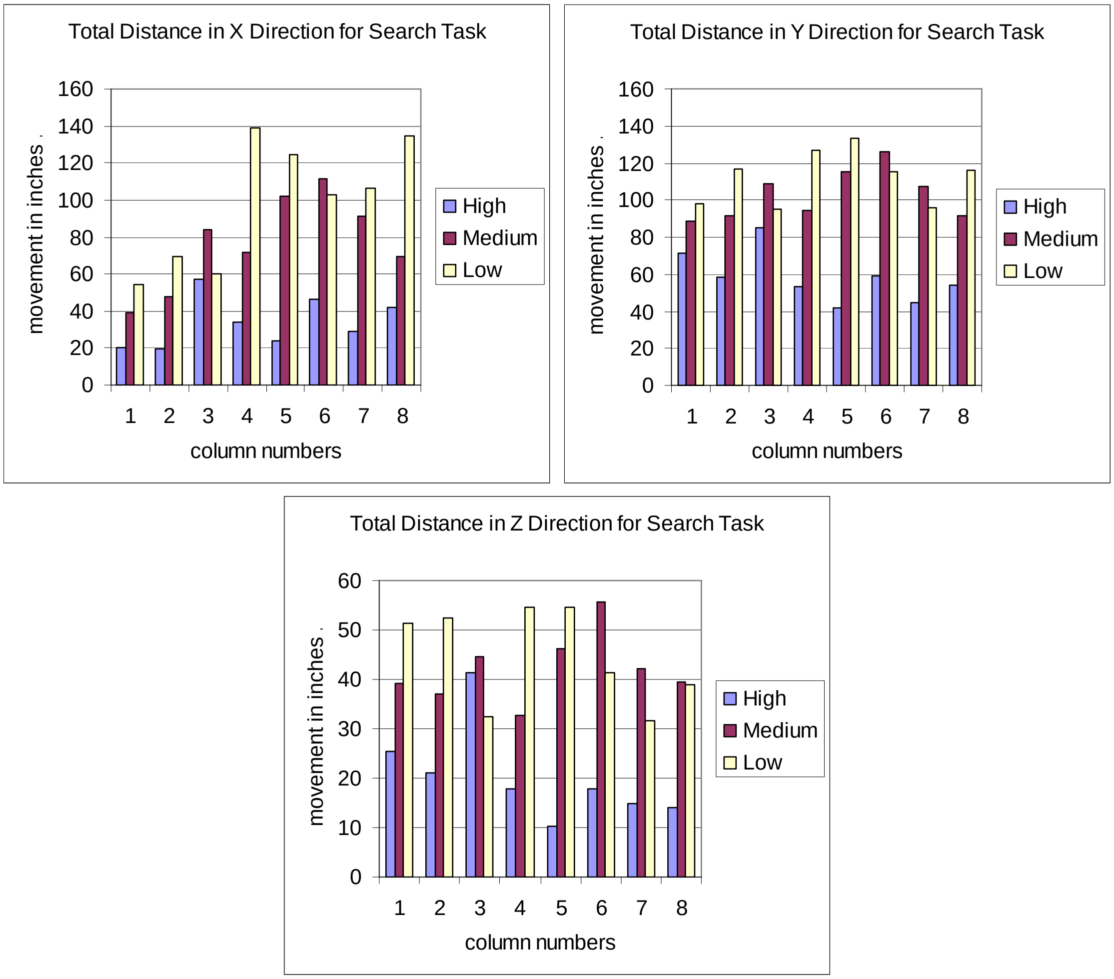


Figure 79. Average total distance of participants in the Y and X axes for the search task.

Over and over it appears that participants chose to make use of greater amounts of physical movement available to them. While participants could have used the same amount of range of movement or total distance as the one column condition on all of the column conditions and simply use the same amount of virtual navigation, the empirical data clearly shows that people prefer physical navigation over virtual navigation.

9.4.3.4.3 Pattern Task Bodily Movement Analysis

For the X range of position ANOVA for the pattern task we found a main effect of task scale ($F(2, 84)=23.7$, $p<0.01$), column width ($F(1,84)=39.4$, $p<0.01$), and an interaction of task scale and column width ($F(2, 84)=12.95$, $p<0.01$). The Y range of position ANOVA found a main effect of task scale ($F(2,84)=8.7$, $p<0.01$) and column width ($F(1,84)=2.85$, $p=0.052$). The Z range of position ANOVA found a main effect of task scale ($F(2,84)=3.69$, $p=0.028$) and column width ($F(1,84)=8.88$, $p<0.01$).

Figure 80 shows the same general trend as the previous two tasks. However, a clear trend that differentiates this data from the navigation and search tasks is the Z-axis data. Figure 80 shows that the one column condition used the most range of movement on the Z-axis on the one column condition, similar to the other tasks. However, an increasing amount of range of movement is seen with the medium (zoom level$_{0.2\text{-}0.4}$) and low tasks (zoom level$_{0.8\text{-}1.0}$) while a decreasing amount is seen with the high task (zoom level$_{0.0\text{-}0.2}$).

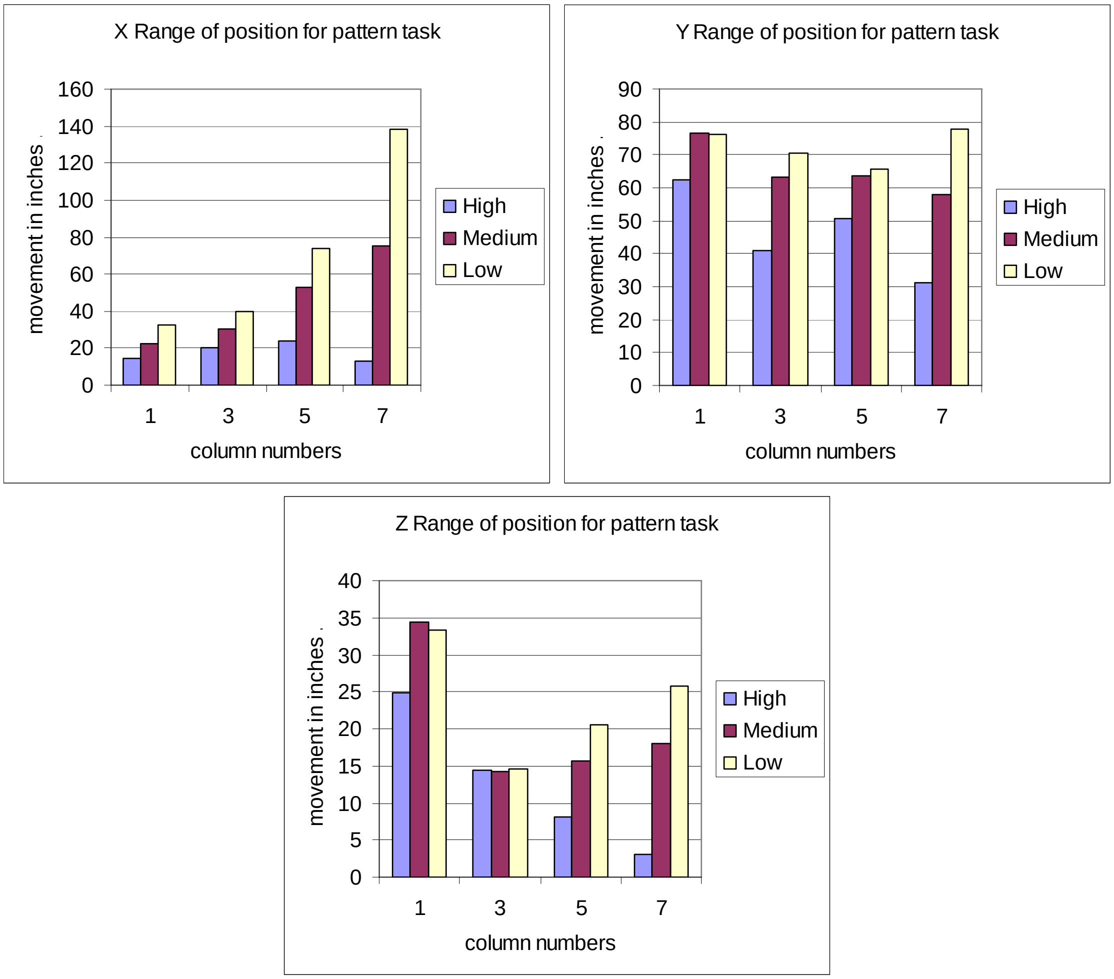


Figure 80. Average amount of range of movement in the X, Y, and Z axes for the pattern task.

The high task can be explained that the task was very simple and that the answer could be found by a glance. However, the other task scales were much harder.

To refresh the reader, the pattern task involved looking through the entire space of data for a particular scale and coming up with an overview for that space. After the special case of the one column condition where participants preferred to maximum their display space and use more of the height (as opposed to using more virtual navigation), more up and down movement was found for increasingly larger viewport sizes.

For the X standard deviation of position ANOVA, we found a main effect of task scale ($F(2,84)=3.46$, $p=0.035$) and an interaction of task scale and column width ($F(2,84)=4.8$, $p=0.01$). The Y standard deviation of position ANOVA found a main effect of column width ($F(1,84)=6.98$, $p<0.01$). However, the Z standard of deviation of position ANOVA found non-significance. Figure 81 shows similar results to Figure 80.

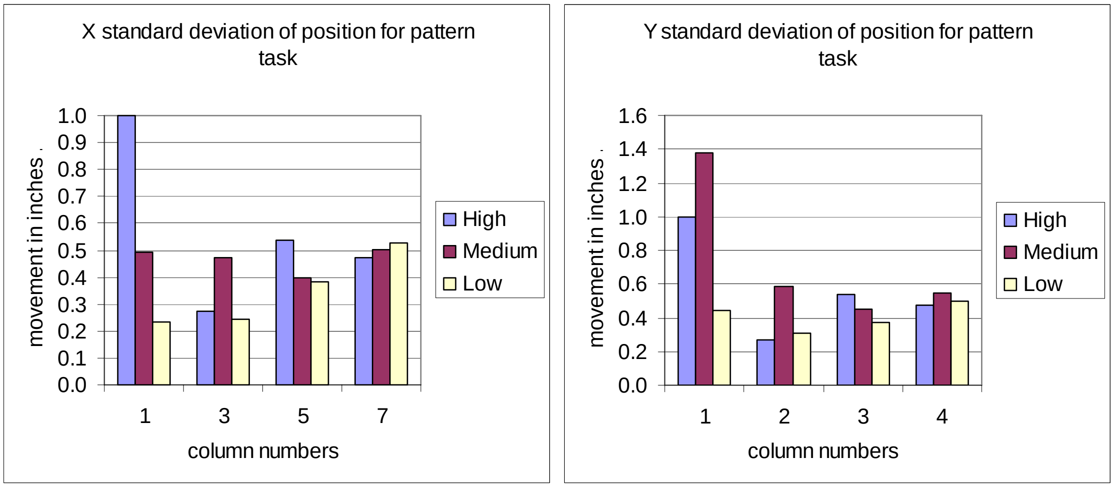


Figure 81. Average standard deviations of position in the X and Y axes for the pattern task.

An ANOVA analyzing the total distance of bodily movement for the pattern task found a main effect of task scale ($F(2,84)=40.66$, $p<0.01$) and a main effect of column width ($F(2,84)=4.84$, $p=0.03$). The X total distance ANOVA found a main effect of task scale ($F(2,84)=44.21$, $p<0.01$), a main effect of column width ($F(1,84)=16.62$, $p<0.01$), and an interaction of task scale and column width ($F(2,7.24)$, $p<0.01$). The Y total distance ANOVA found a main effect of task scale ($F(2,84)=33.52$, $p<0.01$). The Z total distance ANOVA found a main effect of task scale ($F(2,84)=26.52$, $p<0.01$). Figure 82 also shows similar results to Figure 80.

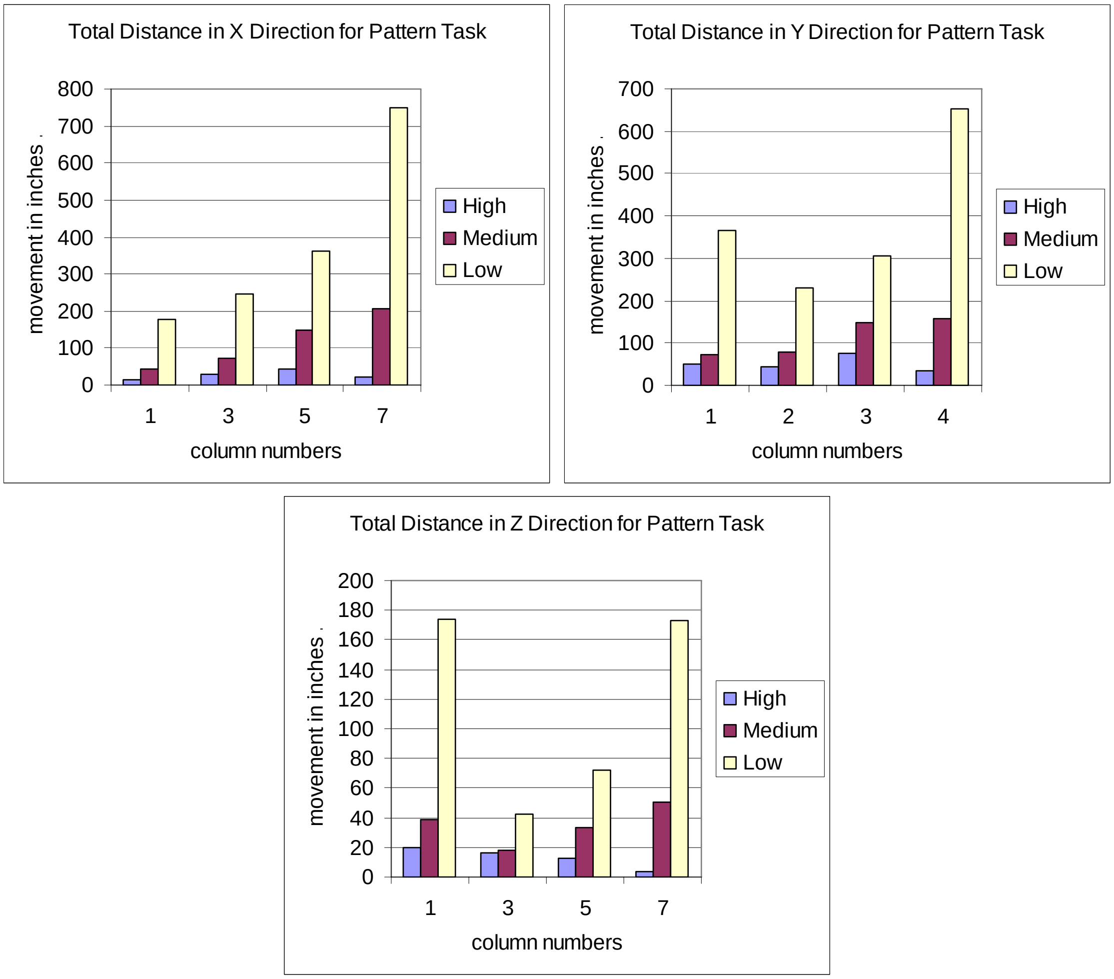


Figure 82. Average total distance of participants in the Y and X axes for the pattern task.

9.4.3.4.4 Insight Task Bodily Movement Analysis

As expected, the analysis of the insight task resulted in few results. The ANOVA performed for the X range of position found a main effect of column width ($F(1,30)=5.6$, $p = 0.024$). However, both the Y and Z range of position ANOVA's resulted in non-significance. Figure 83 shows that the seven column condition used more of the display than the other column conditions.

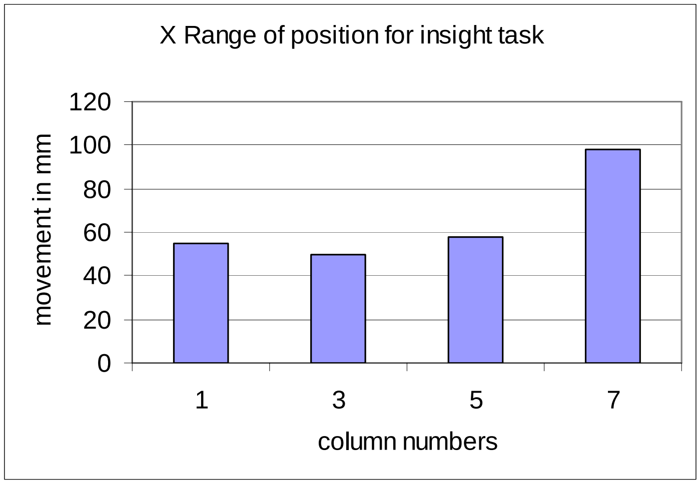


Figure 83. Average amount of range of movement in the X-axis for the insight task.

The reason why the seven column condition is different from the other column condition is that there were a few individuals that participated on the seven column condition that chose to leave the mobile table a few times to see the extent of the large display. However, they seldom did so as that prevented them from quickly writing their answers and therefore they quickly learned to stay at one position.

We argue that one of the reasons that there was no statistical difference found in performance for the insight task is due to the "tethering" effect. By inadvertently requiring participants to stay at one location they could not effectively make use of the entire large display. The mobile stand had the effect of keeping participants at the same location which did not allow them to move around freely. Not being able to move around freely they were not able to resolve as many pixels of the large display. As a result, the larger display did not help them as they could not perceive the data far from them.

The X and Y standard deviation of position both resulted in non-significance. However, the Z standard deviation of position ANOVA found a main effect of column width ($F(1,30) = 5.48$, $p = 0.026$). Figure 84 shows that the one column condition had more variation than the others. This can be explained that the other columns had a much larger display width to work with. However, the one column condition's major asset was height. Therefore, some participants, chose to more fully exploit physical navigation and chose to use more of the height.

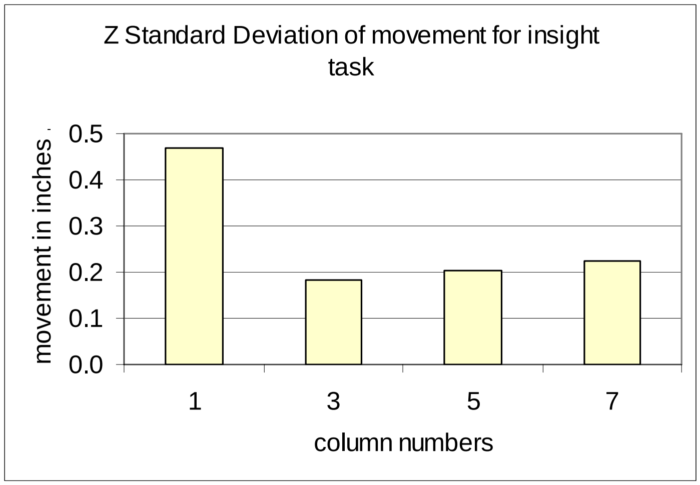


Figure 84. Average standard deviations of position in the Z axes for the insight task.

Analysis of total distance resulted in non-significance for the total distance, the X total distance, the Y total distance, and the Z total distance.

9.4.3.5 Physical Navigation Visualization

In order to better understand the effects of large displays, and better understand the physical navigation results we created visual representations of head/eye gaze projected onto an image of the display.

In order to create the visualization accurately, we mapped generated head gaze of the participants onto an image of the display (see Figure 85). 56 visualizations are the result of the aggregated physical navigation recorded for all the tasks per participant and 1664 total visualizations are the result for all the participants.

Figure 85 is an example of physical movement for the pattern finding task at different column conditions for different participants. Each set of images is for a single participant. The top image is an "overhead camera shot" of the participant involved in the task. The brown line with semicircles represents the stands that held the monitors in place.

The bottom image is the head gaze of the participants. In other words, what is shown is the approximate position of where the participants were looking at with an 87-89% degree of accuracy.

Figure 85 shows four different participants at four different column conditions – one column, three columns, five columns, and seven columns – all for the low pattern task. One can see as the viewport size increases that people naturally take advantage of the additional space. Although each participant had slightly different physical navigation patterns, looked at as a whole, the participants adapted to the larger displays and correspondingly increased their range of physical movement.

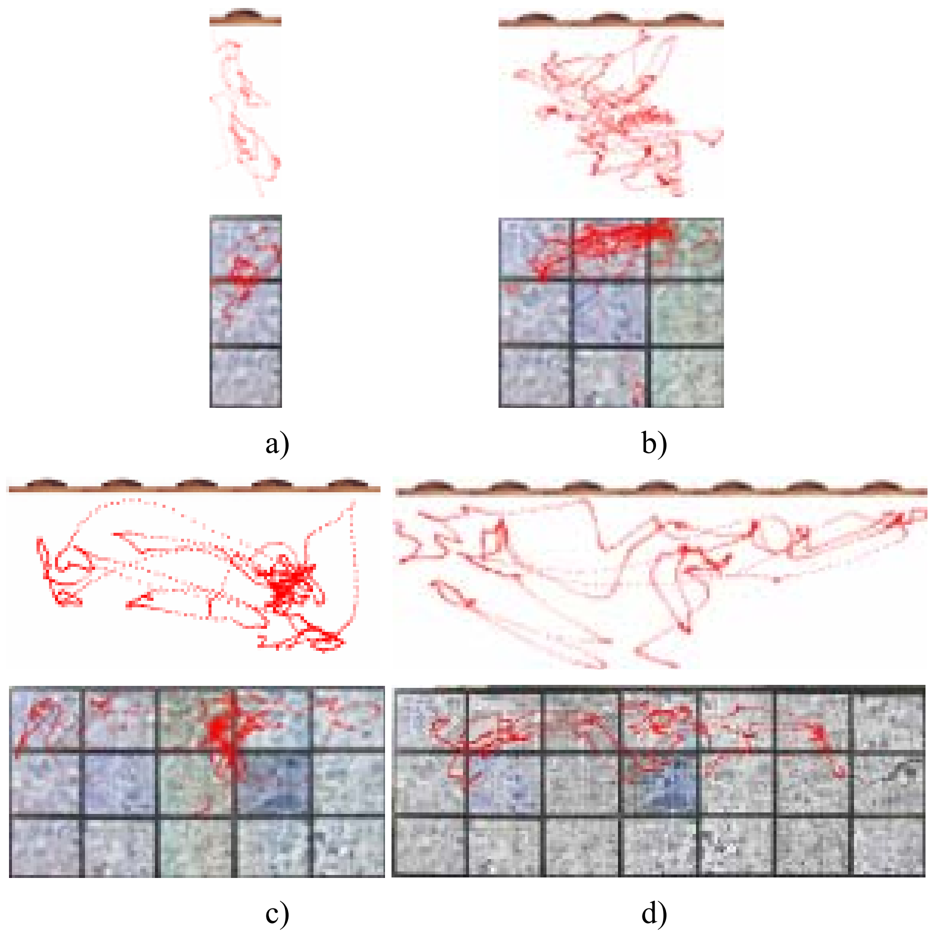


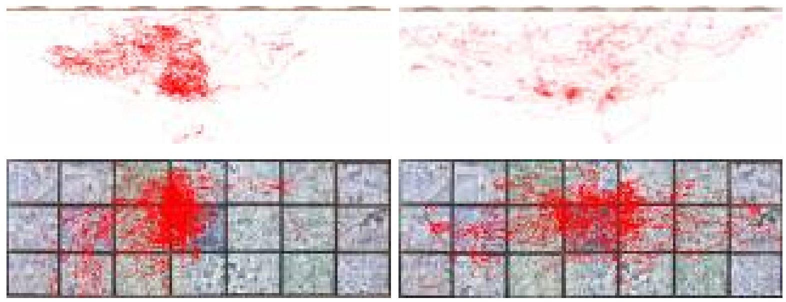
Figure 85. Four different participant data visualizations for four different column conditions. For all image pairs (a-d) the top image corresponds to an "overhead shot" while the bottom image corresponds to where the participant was looking at with an accuracy of about 88%. All four data visualization are for the "low" pattern finding task.

9.4.3.6 Physical Navigation Tethering Visualization

Although more physical navigation is possible with larger displays, logically larger displays do not guarantee more physical navigation. Any physical restraint would have an impact on the actual amount of physical navigation that a person performs.

For example, Bowman, et al. [19] found interesting results forcing virtual navigation in a CAVE environment. They report that after a few episodes of forcing participants to use virtual navigation that participants continued using virtual navigation even when it was not required. In the situation where virtual navigation was not forced, more physical navigation was seen, and performance was higher than when virtual navigation was forced on the users.

In the capstone experiment we gave participants a gyro mouse specifically so that participants did not feel tethered to any particular location. However, for the insight finding task participants were given a mobile lecture stand to write their answers on. Figure 86 shows the physical navigation visualizations for the insight task on seven columns (Figure 86.a) and for the pattern finding task on seven columns (Figure 86.b).



a) b)

Figure 86. Comparison of the insight finding task (a) to the pattern finding task (b). For all image pairs (a-d) the top image corresponds to an "overhead shot" while the bottom image corresponds to where the participant was looking at with an accuracy of about 88%.

For the pattern finding task, there was an average of 340% increase in physical range of movement from the one column condition to the seven column condition. However, for the insight task there was only a 179% increase in physical range of movement from the one column condition to the seven column condition.

As participants physically navigated less for the insight task they also virtually navigated more. The insight task was the only task where non-significance was found for virtual navigation. In other words, there was not statistical difference found in the amount of virtual navigation that took place for that task; no particular display size caused more or less virtual navigation than other display sizes.

Also note that although the viewport size was the same for both tasks, participants' physical navigation drastically differed. One can see in Figure 86.a that the majority of the time participants stayed in approximately the same location due to the need to write on the mobile stand. Compare Figure 86.a to Figure 86.b and see that the physical navigation in Figure 86.b appears far less constrained.

9.4.3.7 Percent of Display Used

An interesting analysis is to understand how much of the display participants used in reference to the amount of range of position exhibited. For example, given a one column viewport, how much of it did they use?

Figure 87 shows the average amount of display used along the x-axis based on the participants range of position divided by the size of the display along. In some cases, such as the one column condition, participants' average range of position was greater than that of the display size. However, the general trend for the search and navigation tasks is that as the display size increases participants used less of the display.

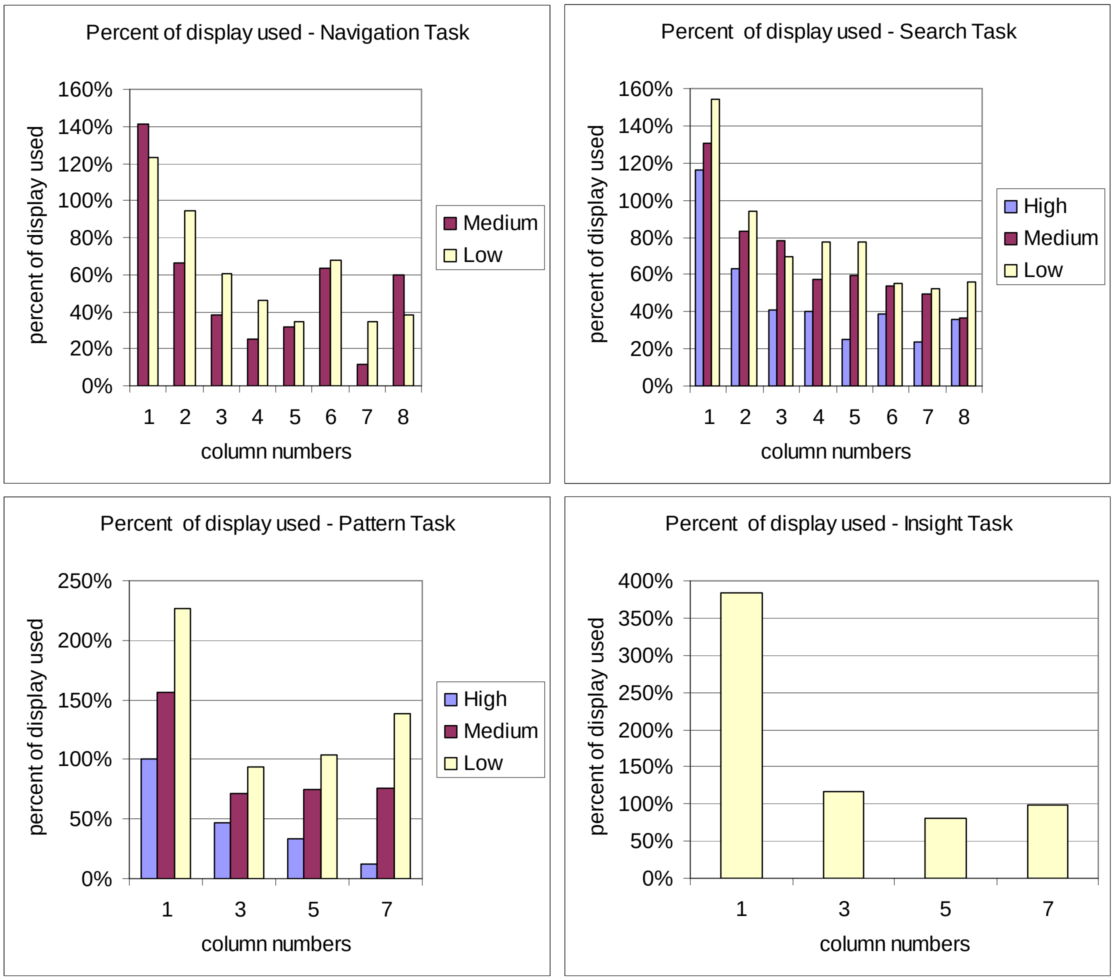


Figure 87. Percent of display used per column number based on the amount of physical x range of position.

However, that is not necessarily the case for the pattern and insight task. Particularly for the pattern task, the same general trend was seen for the high task. On the other hand, the medium task uses approximately the same amount of the display after the one column condition and uses more of the display for the low task after the one column condition.

9.4.3.8 Physical Bodily Movement Conclusions

The analysis of physical bodily movement shows a number of things. First, in general, the larger the display, the more x-axis range of movement and total distance was found. In other words, the larger the viewport size the more participants used it.

For example, the low pattern task (zoom level$_{0.8\text{-}1.0}$) shows an increase in x-axis range of movement of 4.2 times (428%) increase in range of movement from an average of 82 mm of movement for the one column condition to an average of 351 mm of movement for the seven column condition. The total x-axis distance showed a similar result. The increase in total distance was 4.2 times (421%) increase in total movement from an average of 453 mm of movement for the one column condition to an average of 1908 mm of movement for the seven column condition.

Taking the results of all of the tasks together, there appears to be a linear trend of increased x-axis range of movement and total distance covered. This indicates that as the viewport size width increased participants subsequently altered their physical behavior to take advantage of the increased viewport size.

Second, tethering participants to the mobile table had a large effect on their physical navigation which likely affected their performance. Both head gaze and bodily movement were impaired. For example, there was only an increase of 1.79 (179%) of x-axis range of movement from an average of 139 mm for the one column condition to an average of 249 mm for the seven column condition. Comparing the lack of physical navigation variation of the different viewport sizes to the lack of virtual navigation variation, we conclude that the lack of variation of performance was a direct result.

Third, we found that people prefer physical navigation over virtual navigation. This coincides with both the quantitative and qualitative data found in the capstone experiment and all of the initial experiments.

Specifically, we found that people would never stand in one place and virtually navigate first. For example, on the medium navigation task (zoom $level_{0.0\text{-}0.2}$), 100% of the participants (32 out of 32) physically moved to the target without performing any virtual navigation. People had the option of virtual panning or zooming the target closer to them, but none of the 32 participants chose to do so.

Another example can be seen with the first study (with similar observations in all the other studies and the capstone experiment). On the one and four monitor conditions participants would try to squint to see the targets rather than virtually zoom in. This was seen repeatedly by approximately 75% of the participants in the first study.

Other examples, such as in the capstone experiment reinforce physical navigation preference. For example, on the one column condition, regardless of task, participants would walk towards the display. They might start zooming in at the same time (seen in approximately 15% of the participants), but 100% of the participants walked toward the display during the tasks.

Many explanations of physical preference can be seen in the literature. To be brief, it appears that people prefer to use their body for orientation and navigation. Such concepts as proprioception and spatial memory appear to be important factors in helping people in their tasks.

For example, in the first study, for the compare task, participants would often put their finger on a first target while looking for the corresponding pair. This helped participants to not lose the position of the first target. In other experiments, such as the capstone experiment, touching of the display was often seen.

9.5 Capstone Experiment Conclusions

The capstone experiment showed a number of things.

1. It validated with empirical data that there is a definite correlation of virtual and physical navigation to performance, such as with a linear regression showing a correlation of head gaze and the number of virtual zooms resulting in an R^2 is 0.878 and the adjusted R^2 is 0.871.

2. It also showed that semantic zooming and where the semantic zooming thresholds are for the visualization also plays an important role in understanding both virtual and physical navigation. This seems to be especially important in understanding the relationship of performance curves: there appears to be a step-wise linear relationship of performance curves as a direct result of semantic thresholds.
3. As viewport size influences how much virtual navigation is needed in conjunction with semantic zooming we found that viewport size also plays an important role in determining performance time. For example, we saw that performance time can be reduced 10 times (1096%) in the navigation task.
4. Tethering, or being tied to one physical location plays an important role as to how much physical navigation can take place. Regardless of how large the viewport size is the more one is tethered to a location the less of the display one can use. This directly affects physical navigation and therefore affects performance. Specifically, we found no statistical significance in performance for the insight task; likewise we found no real virtual or physical statistical significance either. It is possible that on a curved display the tethering affect would have less of an impact.
5. Task types and task scales exhibit different virtual and physical navigation behaviors and thus exhibit different performance times. Different tasks and different task scales require different semantic zooming levels. As a result, larger viewport sizes will be more beneficial for some tasks and task scales than others.

Chapter 10 Summary Analysis of Data

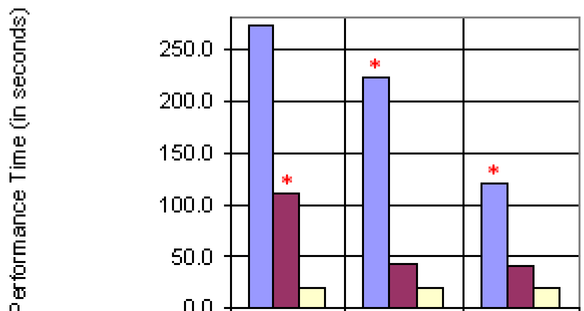
In this section we present an analysis of the four initial studies and the capstone experiment. The section will include general analysis as well as analysis of each particular task.

10.1 General Analysis

10.1.1 Optimality and diminishing returns

Large displays generally help users with performance and accuracy over smaller displays. This was shown both in the capstone experiment as well as the initial experiments. However, there is often a point, or threshold, where performance ceases to improve and gives diminishing returns.

As an example of diminishing returns, consider Figure 88 (a copy of Figure 27 replicated here for convenience) that shows the results from the first study. In that experiment there were three target sizes used (small, medium, and large) on three display sizes (one, four, and nine monitors). For each target size and display size there were two tasks performed: locating a target and locating multiple targets and comparing it to other targets.



	1	4	9
Small Targets	271.6	222.5	121.3
Medium Targets	112.1	42.2	41.0
Large Targets	18.3	19.4	18.3

Figure 88. Copy of Figure 27 to show an example of diminishing returns.

At the start of each task an image was presented at the overview level. Figure 88 (and Figure 27) shows that for the large target size (in yellow) participants did not need to zoom in for more detail. In other words, participants were not required to look at other scales in the space scale as sufficient detail in the overview was seen to perform the task. As a result, one can see diminishing returns beyond the one monitor display.

Similarly, diminishing returns can be seen starting at the four monitor display size for the medium target size (in red). However, for the small target size diminishing returns were not found. Although it is possible that diminishing returns might result after the nine monitor display for that target size and task, larger display sizes would have to be tested to see that result.

This same finding can be found again for other experiments. For example, consider Figure 28, Figure 34, Figure 42, Figure 51, Figure 52, and Figure 53.

As explained before, there is an optimal zoom level for a particular task scale. This optimal zoom level is based on the viewport size and details. The optimal zoom level is the point where the maximum detail can be seen at once for the correct task scale. Any viewport size larger after the viewport size that allows the most amount of details to be shown at the optimal zoom level results in diminishing returns.

However, diminishing returns may result from other factors such as the design of the visualization in conjunction with display size. For example, the capstone experiment shows different performance curves at various thresholds.

In this particular example, Figure 57 shows the performance time for the navigation task for the medium space-scale task with different semantic zooming thresholds superimposed. From Figure 57 we see that semantic zooming thresholds also are a strong factor in determining the optimal zoom level and diminishing returns. This is especially since the semantic zooming thresholds dictate when the details are shown playing a role in determining where the optimal zoom level is for a task scale.

10.1.2 Perception

As the objective of the participants was to perceive a certain amount of data, it can be said that the participants' perception was being greatly hampered by the smaller viewport sizes. As the viewport sizes increased to encompass more of the participants' field of view, the participants' eyes and body were being better utilized. Obviously, the smaller viewport sizes were not taking advantage of the participants' perceptional and cognitive abilities.

10.1.3 Memory

The process of cognitive analysis is complex at best. However, any step or process that can be shortened to reach a conclusion will help decrease performance time. In addition to navigation, large viewports help with memory.

Large displays take advantage of external memory. External memory, or external memory aides, extends the limits of working memory beyond seven chunks (objects). Miller's well-known paper explains that people are only able to keep seven, plus or minus two chunks, or objects, in working memory at a time [90]. However, externalization, the process of putting a visible form of our thoughts on paper or a computer screen, extends working memory by using the environment, such as paper or a computer screen, to keep track of more than seven chunks [64].

By taking advantage of spatial memory and external memory, people are able to quickly look at large areas of detail and quickly remember the details without necessarily having to memorize them. By remembering that "the expensive one was over there" people can use external memory and spatial memory together to overcome having to remember short term items. In other words, by having a greater amount of information on the display at once, one can remember that certain areas are more expensive than others. People do not need to remember exactly what the prices were as they can quickly refer back to them as they are still present.

A common solution for comparison tasks that require large amounts of virtual navigation is to write down the first answer on a piece of paper, an external memory aide, before proceeding to the second area of comparison. By doing this, one externalizes the information received for the first part of the task. Without doing this the person has to concentrate on both remembering the information and virtually navigating. Far too often, without writing down the answer, the act of extensive virtual navigation causes a person to forget the first answer that was held in short-term memory.

By having a smaller display people are required to use more short-term memory to remember either the virtual position of areas of detail or remember the details themselves. Neither spatial nor external memory is utilized efficiently. More cognitive effort is spent navigating to the different areas of interest.

10.1.4 Curved versus Flat and Muscle Groups

The results from our fourth study show that participants were able to use twenty-four monitors the most effectively when it was curved. By not having to walk, but simply swivel in their chair, they could quickly physically navigate the large display.

In addition, besides the ability of participants to quickly access information from one side of the display to another, a curved display offers a longer utility of the display for people in the long run. By not using large muscle groups such as the legs and back to navigate as much, the curved displays uses smaller muscle groups, such as in the neck, which fatigue more slowly.

An example of small versus large muscle fatigue is typing versus walking. Where typing uses small muscles in the forearms most people are able to type for an extended period of time before feeling fatigue; walking, on the other hand, fatigues faster.

This long-term utility was most obviously observed in a longitudinal study that we performed on the usability of large desktop displays [8]. Our results showed that given a flat, large display for a desktop only part of the display was used frequently. Interestingly, the parts of the display that was not used were the edges of the display as they were physically distant from the users. Based on the fourth study more of the display would have been used if it were curved.

10.2 Task Analysis / Theoretical model

This section presents a theoretical model that helps explain how performance time relates to viewport size and the space-scale model. As, [63] points out, theory does not apply to any specific situation, but helps understand and predict any future situation.

The rest of this section explains how different factors influence performance time for different tasks. This analysis is based on the different experiments presented in this dissertation.

10.2.1 Navigation Task

Navigating from one point in space scale to another involves virtual and physical navigation. First, a person must virtually navigate if the target cannot be perceived at the given scale. Second, a person must physically navigate in some form with physically moving their eyes if nothing else.

As viewport size increases the data shows that performance time decreases. However, is the decrease in performance time due more to the decreased amount of virtual navigation, the increased physical navigation, or increased perception abilities? Also, one might question the purpose of navigation. Is navigation nothing more than a method of moving the eyes to be able to perceive the data?

We argue that physical navigation is more than just a method for moving one's eyes. First, if physical navigation were the same as just moving one's eyes, then people should be able to perform as well on a small display with virtual panning as physical panning – but that is obviously not the case based on our empirical results.

Second, physical navigation is not the same as just a method of moving one's eyes with virtual navigation because such things as spatial memory, and proprioception play a part in helping people reduce their performance time. For example, moving one's head helps orient a person and helps with the use of spatial memory. Also, walking or moving one's head is natural. People are experts at it – they have been doing it their entire life. People are able to effectively move their head with little cognitive effort. Although physical navigation such as walking may be more inefficient in terms of effort, moving one's head side to side often is not.

Therefore, navigation is not just a tool for moving one's eyes in space scale, but a tool for helping to orient and move their eyes effectively. Also, we have shown that physical navigation is both preferred and more efficient than virtual navigation.

Understanding that navigation is more than moving one's eyes, what factors are involved with navigation? First, field of view affects navigation. Additional information and better optical flow help orient the user [32].

Virtual navigation also affects navigation's performance time. If one has to virtually navigate then one has to spend the additional effort and time to pan and/or zoom to the desired target until the details can be seen based on semantic zooming. As a note, the additional screen space from a larger viewport size helps with navigation in two ways: First, the larger the viewport size the less one has to virtually pan or virtually zoom to get to the target. Second, the larger the space available for small navigation errors, the faster and less precise a person needs to be when navigating.

Semantic zooming level affects navigation. The deeper the semantic zoom level one is interested, the longer it takes to virtually navigate to it.

Physical navigation also affects navigation. The faster one can physically get to the point of interest, the faster they can finish the task. As seen from all the initial studies and the capstone experiment, participants prefer to physical navigate over virtually navigate. For example, from the first and second studies participants were found to squint at display over virtually navigating.

Another example is where participants in the capstone experiment *always* walked closer or further from the display before virtually navigating. Even with the high pattern task (zoom $\text{level}_{0.0\text{-}0.2}$) on the seven column condition where participants zoomed out to better see the overview, they stepped back first.

Viewport size itself only affects things indirectly as already explained above. Viewport size only affects navigation in that it affects virtual and physical navigation and semantic zooming.

As a result, for the navigation task purposes, the larger the viewport size the less virtual navigation is performed, and the more physical navigation becomes the key predictor of performance time. So,

As viewport size increases do too does the field of view and it is logical that decreased virtual navigation and increased physical navigation occur and therefore performance time decreases:

$$\begin{aligned}
&\uparrow ViewportSize \Rightarrow \\
&\uparrow FieldOfView \Rightarrow \\
&\downarrow VirtualNavigation \uparrow PhysicalNavigation \\
&\therefore \\
&\downarrow PerformanceTime
\end{aligned}$$

The implications of this equation are that as viewport size increases then performance time reduces to a function of the time it takes to physically move to a position where the data can be perceived. Thus, the time it takes to navigate to a point can be reduced to a few seconds with a viewport size that is large enough to see all details of the zoom level that one is interested in.

On the other hand, as viewport size decreases then performance time reduces to a function of the time it takes to virtually navigate the space and scale to the desired position. Thus, the smaller the viewport size, the more the performance time becomes a function of the optimality of the zooming and panning functions as well as the user's ability to be precise in his navigation. For a large data set, a small viewport size, and sub-optimal zooming and panning algorithms, the time it takes to navigate to the point of interest may take minutes to complete.

It should be noted that the smaller the viewport size the harder it is to be accurate in virtual navigation. For example, in the capstone experiment participants were often seen to navigate and lose sight of the target on smaller viewport sizes, such as the one and two column condition. As a result extra time was needed to get reoriented and navigate to the target.

In conclusion, navigation's performance time can be estimated as a function of the time it takes to physically navigate to the target with an increasingly larger viewport size or as a function of the time it takes to virtually navigate to the target with an increasingly smaller viewport size.

10.2.2 Search Task

Searching for a single target involves navigating to potential areas of interest, deciding if the target ($object_i$) has been found, then stopping as the task is finished or repeating the process of navigating and deciding until the target is found.

Unlike the navigation task, the person's field of view for the search task is important. Intuitively, the viewport size, the greater the field of view, the more one can see at once. The more one can see at once, the greater the chances of finding the $object_i$ that meets the search criteria.

Virtual navigation affects the search task in a similar way as the navigation task. First, one must reach the zoom $level_j$ that corresponds to the appropriate amount of detail as dictated by the semantic zooming. All time spent on initially reaching to the desired zoom $level_j$ is time wasted on non-productive navigation. Second, the more one has to pan to search for the $object_i$ the more one has to focus on virtual navigation, which is less natural and takes more time to perform than physical navigation.

Physical navigation also affects search. The more one can quickly glance through a series of objects, the quicker one can find an $object_i$ that meets the search criteria. In addition, the larger the viewport size the more one can use spatial memory to remember where one has looked.

There is also a greater amount of thought, or cognition, which takes place with the search task over the navigation task. As shown in earlier experiments as well as in the capstone experiment, people are able to naturally use better global strategies when they see more details in conjunction with a larger overview. For non-random data (such as used in all but the first experiment), people are better able to guess where an $object_i$ that meets the search criteria is likely to be.

For example, with the second experiment participants were able to use better heuristics to guess where a university would be located. The third experiment showed that participants exhibited different attack strategies using more global strategies that proved to be better for winning. The capstone experiment showed that participants were able to quickly search in clusters of similar houses when they had larger viewport sizes as opposed to randomly looking for a house in smaller viewport sizes.

In summary, people are able to search for objects better with larger viewport sizes because they are able to have a larger field of view which helps strategize better, use less virtually navigation, and use more physical navigation.

As viewport size increases it is logical that field of view increases which in turn helps people perceive more data at once, which leads to better search strategies, which helps people use less virtual navigation, more productive physical navigation, which decreases performance time.

$$\begin{aligned}
&\uparrow ViewportSize \Rightarrow \\
&\uparrow FieldOfView \Rightarrow \\
&\uparrow GlobalStrategies \Rightarrow \\
&\downarrow VirtualNavigation \uparrow PhysicalNavigation \\
&\therefore \\
&\downarrow PerformanceTime
\end{aligned}$$

The first thing to note about this equation is that the implications of the navigation equation are added within the equation. So, a small viewport size with a large dataset and sub-optimal algorithms for zooming and panning will add time to each navigation subtask. In other words, each time a user investigates a particular point of interest it will take additional time to get to that point.

In addition, the experiments presented in this dissertation show that people are more random in their search tasks with smaller displays as they are not able to as quickly create a larger overview mental model of the data. As a result, on a smaller viewport sizes it could take a person hours to find an object that meets the search criteria.

On the other hand, as viewport size increases people are able to make better guesses, or heuristics, as to where to look. In conjunction with navigation that takes less than a second to navigate to a point of interest, if a user guesses correctly at his search subtask (navigating to his first point of interest), then he may find an object that meets his search criteria immediately. Thus, minimally, it will take less than a second to find.

In conclusion, a search task performance time can be estimated as a function of the time it takes to navigate to points of interest. Also, the points of interest become increasingly pertinent to the search task as people are able to make better heuristics about where the search criteria will be met as the viewport size increases. In summary, the larger the viewport size, the better able people are to make heuristics as to where to navigate, decreasing the number of navigation subtasks and the faster the navigation subtasks take to perform.

10.2.3 Comparison Task

A comparison task is either a task that involves searching for two objects that meet the same search criteria or navigating to two points of interest and comparing them.

The first study had a task like the first case. It involved finding pairs of the same geometric shape. Participants were required to search for the pairs and report their positions.

However, the second case, that of simply navigating to two points of interest and comparing them, was often prevalent. A participant would search for pairs, find one of the two shapes and then later find the other pair. However, they would often forget where the first shape was and would have to re-navigate back to the first shape to verify that they were in fact the same geometric shape.

In either case, a comparison task can be thought of as a set of search and navigation subtasks with a set of cognitive comparison subtasks.

As a result, the field of view, semantic zooming, virtual navigation, and physical navigation all play important roles. However, additional factors that also play important roles are spatial memory and external memory.

As explained above, the larger the viewport size, the greater the ability for people to use their spatial memory to remember where on the display the other shape might be. In addition, external memory plays a role in that participants need not remember exactly what they saw, but that it was “over there.”

This was especially important for the largest viewport size used in the first study. Participants often found the first of a particular geometric shape and then would continue to look for the other. While looking they may see several other geometric shapes that did not match. However, when they found another one they could quickly refer back to the first shape found (using spatial memory) and compare the shapes without having to remember exactly which shape they have previously seen (using external memory).

In summary, people are able to perform comparison tasks faster with larger displays because they have an increased field of view which allows to make better use of spatial memory and external memory which helps strategize better, use less virtual navigation, and use more physical memory.

As viewport size increases it is logical that field of view increases which in turn helps people perceive more data at once, make use of spatial and external memory, which leads to better strategies, which helps people use less virtual navigation, more productive physical navigation, which decreases performance time.

$$\begin{aligned}
&\uparrow \mathit{ViewportSize} \Rightarrow \\
&\uparrow \mathit{FieldOfView} \Rightarrow \\
&\uparrow \mathit{SpatialMemory} \uparrow \mathit{ExternalMemory} \Rightarrow \\
&\uparrow \mathit{GlobalStrategies} \Rightarrow \\
&\downarrow \mathit{VirtualNavigation} \uparrow \mathit{PhysicalNavigation} \\
&\therefore \\
&\downarrow \mathit{PerformanceTime}
\end{aligned}$$

Similar to the other equations, this equation has in it subtasks. Specifically, it includes navigation and search tasks with it.

10.2.4 Pattern Task

A pattern finding task is a task with the goal of summing up an overview of a certain detail or set of details. Exactly how people are able to find patterns in data is an active research topic in psychology and will not be discussed here. There are many different factors of pattern finding from visual learning, visual templates, visual aggregation, experience with pattern finding, etc. [42]. However, for the simplest case, a person finds a pattern by performing a range of comparison tasks.

Exactly how much of a dataset a person needs to look over to perceive the correct pattern is unknown. In the case of the capstone experiment it appeared that participants looked at the majority of the data to obtain the correct pattern.

The factors that we found that pertain to pattern finding include all the ones that pertained to the comparison task. For example, with field of view, similar to searching for a task the more one can see all of the details the faster one can find the overall pattern. The difference is that one must aggregate details in one's mind to find overall patterns, thus using more of the overview. The more shown, logically, the faster one can come up with a pattern.

External and spatial memory affect pattern finding. The larger the viewport size, the more one see at once. Consequently, one can summarize areas and remember where the areas are using spatial memory. In addition, using external memory one need not retain as much in short-term memory as one can quickly look back at the previously explored areas to remember the details like in the comparison task. However, instead of using spatial and external memory to remember one object people can use to help them remember their mental model of an area.

Virtual navigation affects pattern finding the same as it affects comparison tasks. One must reach the zoom $level_j$ that corresponds to the appropriate amount of detail as dictated by the semantic zooming. One must pan the entire area (or perform a series of zooms) to understand the entire pattern.

Physical navigation also affects pattern finding in that the quicker one can perceive all the desired details, the quicker one can cognitively create the pattern. One cannot perceive a pattern in the data until one sees it.

Results from the capstone experiment show that when all of the details are shown then the size of the viewport does not matter. Specifically, the pattern high (zoom $level_{0.0\text{-}0.2}$) and pattern medium (zoom $level_{0.2\text{-}0.4}$) tasks from the capstone experiment showed all of the details that one needed for all the column conditions used. As a result, there were not any statistical differences in performance times. When all the details that are prevalent are shown then the viewport size is irrelevant; what is important is the ability to quickly perceive all the details needed to complete the task.

The equation for the comparison task is the same for the pattern task. The main difference is the amount of data being compared and the cognition that takes place in the person's mind.

As viewport size increases it is logical that field of view increases which in turn helps people perceive more data at once, make use of spatial and external memory, which leads to better strategies, which helps people use less virtual navigation, more productive physical navigation, which decreases performance time.

$$\begin{aligned}
&\uparrow \mathit{ViewportSize} \Rightarrow \\
&\uparrow \mathit{FieldOfView} \Rightarrow \\
&\uparrow \mathit{SpatialMemory} \uparrow \mathit{ExternalMemory} \Rightarrow \\
&\uparrow \mathit{GlobalStrategies} \Rightarrow \\
&\downarrow \mathit{VirtualNavigation} \uparrow \mathit{PhysicalNavigation} \\
&\therefore \\
&\downarrow \mathit{PerformanceTime}
\end{aligned}$$

In summary, people are able to find patterns with larger viewport sizes. However, several things need to be pointed out. It is apparent that cognition plays a large part in finding patterns. Larger viewport sizes help in perceiving more data faster than smaller viewport sizes if the larger viewport sizes help with seeing more data at the appropriate zoom level. There is a large amount of cognition that takes place that is beyond the scope of this paper. However, the following can be claimed:

1. Larger viewport sizes help people perceive more data at once at lower zoom levels.
2. Larger viewport sizes help with spatial and external memory that helps people aggregate data.

10.2.5 Insight Task

How people are able to achieve insight into data is an active research topic in the field of psychology. However, I define insight to be undirected patterns that people are able to find. As a result, I suggest that people can benefit from larger viewport sizes much the same way as they can from pattern finding tasks (see section 10.2.4).

Chapter 11 Conclusion

11.1 Contributions

This dissertation contributes to the fields of human-computer interaction and information visualization in that it explains how viewport size, task, task scale, semantic zooming, freedom of movement of interactive devices (e.g. tethering), virtual navigation, physical navigation, and perception (including field of view) all contribute in understanding how viewport size affects human behavior with geospatial visualizations. This dissertation especially contributes in that it takes the mystery out of performance improvements for large viewports. As a direct result researchers and practitioners can better create visualizations and understand the impact of performance of their visualizations with large viewports.

Specifically, this dissertation shows a general improvement of two to three times performance improvement for geospatial tasks with larger viewport sizes. It also shows more than a ten fold performance improvement in simpler tasks, such as navigation with an eight times larger viewport size.

This dissertation explains how there is a virtual to physical navigation tradeoff with viewport size. We defined virtual navigation to be computer input, such as from a mouse or keyboard and physical navigation to be bodily movement that supports the task.

As the viewport size increases there is an inverse relationship between virtual and physical navigation. In other words, as viewport size increases people use less virtual navigation and more physical navigation. A linear regression of virtual navigation and physical navigation to performance (specifically the number of zooms and the head gaze) resulted in an R^2 is 0.878 and the adjusted R^2 is 0.871.

In addition, we consistently observed preference of physical navigation over virtual navigation. For example, in one case where either virtual navigation or physical navigation was on option, 100% of the participants (32 out of 32) chose to completely use physical navigation and not use virtual navigation.

In addition, we observed numerous situations where participants chose to perform uncomfortable, fatiguing physical navigation over virtual navigation, such as in the third study. Specifically, participants consistently used all nine monitors in the third study while sitting even though sitting and using the top row of monitors is uncomfortable and fatigues the neck after a period of time.

Concepts such as proprioception and spatial memory play a large role in preference to physical navigation over virtual navigation (e.g. [19]). Participants were often seen and explained in their own words, that they would rather navigate in a more "natural" manner than get lost by performing virtual navigation. This is confirmatory evidence for the concept of embodied interaction in which human bodily resources are effectively exploited.

In our extension of the space-scale concept we explained that with larger viewport sizes there exists greater freedom to choose between physical and virtual navigation. Given the correct semantic zoom level to see the desired details of a task, people have a choice to make either physical or virtual navigation. The smaller the viewport size, the less people have a choice; the more they are required to use virtual navigation to navigate the space.

For all the initial studies and the capstone experiment we found that participants chose to first physically navigate before virtually navigating. For example, with the first and second study, participants would choose to squint at the display to see if they could complete the task without virtual navigation; then, and only then, would participants perform virtual navigation if they found that squinting did not help them perform their tasks. In other words, after participants had exhausted the effectiveness of physical navigation did participants virtually navigate.

However, we observed two instances where virtual navigation was preferred to physical navigation. In both instances, one from the fourth study and one from the capstone experiment, we observed that participants' interactive device was limiting their mobile freedom. As a result of being "tethered" to a particular location we qualitatively observed in the fourth study experiment and qualitatively and quantitatively observed in the capstone experiment that people did not physically navigate as much as a direct result.

For comparison sake, in the capstone experiment, the amount of physical range of movement in the x-axis is only 179% greater for the largest viewport size tested compared to the smallest viewport size for the "tethered" task in the capstone experiment. On the other hand, a similar "non-tethered" task (the pattern task) showed a 428% increase in x-axis movement for the same viewport size conditions.

As a result of both the theoretical related work and the empirical evidence gathered by this dissertation, we conclude that for non-tethered tasks participants prefer physical navigation over virtual navigation. This preference leads to a decrease in virtual navigation as a result of the inverse relationship of virtual and physical navigation. This subsequent decreased virtual navigation and increased physical navigation allows people to take better advantage of their body's abilities which include spatial memory and proprioception to partially explain the decrease in performance time.

Another explanation of improved performance time is due to increased awareness of both the details and the overview of the geospatial visualization. By having a greater perception of the overall space and scale people are able to create better heuristics for individual tasks. For example, we found that people were able to more logically search for targets, such as in the second study. Participants were more logical and less serial in their searching for items than on smaller viewport sizes. For instance, when asked where a university was, participants on the smaller viewport sizes were observed to serially look through the entire display. However, on the largest viewport size participants were observed to look at the overview of the map first and then look at logical geographic locations that a university might be located.

As another example, we found that participants created better global strategies on the third study to help them win the game. Participants were generally more proactive about their attacks with the larger viewport sizes than the smaller viewport sizes where participants were generally more reactive.

These better strategies were also seen in the capstone experiment where people were observed to search for individual targets or patterns with more focus. In other words, participants on the smaller viewport sizes were more random about their tasks, thus worsening their performance times. However, participants on the larger viewport sizes were more focused in that they more directly navigated to particular areas of the map that appeared from their greater overview and detail perspective to be a better location to search.

Combining the increased physical navigation with decreased virtual navigation in conjunction with better heuristics and strategies helps explain performance improvements with larger viewport sizes. However, two essential factors that must be mentioned are task scale and semantic zooming.

The task scale of the task dictates at what scale a person must be minimally zoomed in to perform the task. This required scale comes from two factors: detail level and semantic zooming.

For any particular task, there is a minimal level of detail that is sought. For example, in the capstone task, a medium scale task required participants to look at house prices. The task could not be completed without zooming into the scale that shows house price. Semantic zooming is involved as the semantic zooming thresholds dictate at what scale different details are shown.

We have shown that performance is related to virtual and physical navigation. However, as the amount of virtual navigation that is required is based on semantic zooming, performance is affected indirectly by semantic zooming through virtual navigation.

The result is that performance of geospatial tasks with semantic zooming (as opposed to geometric zooming) results in step-wise linear performance. In other words, within each semantic threshold (the point along scale where the view changes) there is a linear improvement of performance as viewport size increases. At the thresholds, there is a large step in improvement. The different parts or segments have different slopes. Outside a particular semantic threshold there are different performance lines.

The general trend is that starting from a small viewport size and increasing to a larger viewport size that performance improves and that there are different linear performance improvements with different semantic thresholds. However, it appears that the slope of each subsequent step, or transition to the next semantic threshold, is less steep than the previous performance line.

We have also shown that the affects of viewport size with semantic zooming add additional complexity, or more possible analyses to tasks with the option of using visual aggregation. Computational aggregation, aggregation automatically performed by computers, is available for all viewport sizes. However, visual aggregation, where people use their eyes and mind to aggregate the data, is more available for larger viewport sizes.

With visual aggregation people are able to look at larger spaces of the data for a particular scale with larger viewport sizes. This is possible due to the additional pixels presented and the additional physical navigation.

Lastly, we have shown that participants' behavior (their performance, virtual navigation, and physical navigation) differs from task to task and from task scale to task scale. We repeatedly saw from our statistical results differences between tasks and task scales. In other words, we repeatedly saw different tasks result in different performance curves and different task scales differ in performance curves within the same task.

People use different amounts of virtual and physical navigation for their varying tasks. One task may require large amounts of detailed comparisons. Another task might require large overview pattern analysis. As a result, the performance, virtual navigation, and physical navigation exhibited by people would be different.

As a result of these tasks and task scales exhibiting different behavior it is not justifiable to state that larger viewport sizes always help with all tasks and task scales. Indeed, it appears that larger viewport sizes help only when they better fit the needs of the task and task scale.

Generically speaking, it appears that larger viewport sizes do not generally help improve performance after the point where all the details that a person needs to complete a task are visible thus resulting in diminishing returns. For example, with the capstone experiment the performance for the overview (high) tasks did not improve with larger viewport sizes as all the detail needed for the task could be seen on the smallest viewport size tested.

However, the faster one can access all the appropriate details for a given task, the faster one can complete one's task. The faster one can perceive all the data that is needed for the task, the faster the task is performed. Indeed, with some cases larger viewport sizes dramatically increase performance. For example, we found more than a ten fold increase in performance for the medium navigation task in the capstone experiment.

As a result, the more virtual navigation needed to access all the details, the longer the task will take. On the opposite extreme, the less virtual navigation required, the more a person can use physical navigation in conjunction with using spatial memory, proprioception, and better heuristics and strategies to help perform tasks, which leads to better performance.

In conclusion, larger viewport sizes generally help decrease performance time over smaller viewport sizes due to people's ability to better utilize their cognitive and physical resources. The more people can use their eyes, mind, and body, the faster they are able to complete a task.

11.2 Future Work

There is a large area of research that can be done to improve our understanding of how human behavior changes with increased viewport size. A few of the more prominent ones are listed here:

1. Different densities: How do different pixel densities affect human behavior and performance? For example, all the monitors used in the experiments explained in this dissertation used the same pixel density. However, how would a denser density display affect performance?
2. Bezels: Although some initial work on understanding bezels has been done by Mackinlay, et al. [83], there is more work that needs to be done on the cognitive aspects of bezels. For example, how do bezels and their distortive affects affect accuracy and performance?

3. Form factors and ergonomics: Larger displays are inherently larger physically. However, does this pose a problem with physical abilities?
4. Multi-scale: The experiments in this dissertation have addressed only single scale tasks. How do the results from experiments with multi-scale tasks differ from those outlined in this dissertation?
5. Multiple views: With additional space there are numerous opportunities for having multiple views of data. What types of techniques and paradigms would lead to the best performance and insight of the data?
6. Abstract visualizations: As abstract visualizations do not have an inherent spatial view, what would the best visualization designs for the larger viewports? Are there differences in how people interact with abstract visualizations? Can the results from this dissertation be extrapolated for abstract visualizations?
7. Data and eye gaze: What parts of a visualization do people look at more? Most importantly, what parts of a visualization do people look at to generate an accurate mental pattern of the data?

11.3 Generic Spatial Visualization Extrapolation

Although the experiments performed for this dissertation were mostly done with geospatial visualizations, we believe that the results have a wider impact that reaches a broader area of information visualization. We particularly believe that the results from the experiments also extrapolate to spatially oriented visualizations.

First, in order to understand how the results can be extrapolated, we must understand what constitutes a geospatial visualization. We can then identify what aspects of geospatial visualizations are similar to other visualizations.

A geospatial visualization is one where there is a geo base, or earth component, as the underlying view. This geo base is shown as a map that represents either a real or fictitious location on earth (or similar planetary location - such as mars) with or without a 3D terrain component. The information visualization aspect usually involves superimposing visualizations (e.g. glyphs, lines, charts, etc.) on the geo base.

The visualizations superimposed on the base represent a strict spatial positioning with respect to other visualizations on the base. Distances, orientations, and positions of visualized objects all have meaning in a geospatial context. For example, an object visualized north of a second object has an implicit meaning of being north of the second object. This should not be confused as the second object being "above" the first object, but north in strict meaning of a compass as the second object might actually be "below" the other object depending on perspective.

On the other hand, a more generic spatial visualization is a visualization that has spatial meanings to other objects but not to a particular base. As a result, the terms of north, south, east, and west do not have the same meaning. An example of a more generic spatial visualization is the visualization of dots used in the first study. Common examples include general node and like graphs and visualizations such as Pad++ [15] and Data Mountain [118] .

For example, if one were visualizing Washington, D.C. with a geo base then one could say that the White House is east of the US Capitol. This would be true regardless of the orientation of the map (whether east were up, down, left, or right) as the geo base of the visualization dictates direction. On the other hand, if one were visualizing the business organization charts (a type of node and link graph) of the White House and the US Capitol then showing a particular person "east" of another person is not meaningful.

However, both geospatial visualizations and generic spatial visualizations have an inherent spatial orientation. For example, with a business organization chart, if the highest ranking person is located at the top of the display, then one could say that all other people below that person is ranked lower than him. Also, the "farther away" a person is from another person the further removed they are from the other person in terms of rank.

Although distance does not mean the same thing for geospatial visualizations as generic spatial visualizations, they still have some form of meaning. Indeed, if distance and space is not relevant, then it is not a spatial visualization.

The tasks used in the different studies in this dissertation include both geospatial specific tasks and generic spatial tasks. Geospatial specific tasks include route finding, route tracing, map comparisons (differences between old and new maps), and counting geo base objects (objects that are part of the map). These tasks are specifically geospatial in nature and may or may not extrapolate to more generic spatial tasks. These specific tasks were only performed in two studies: the second study and the fourth study.

However, the majority of the tasks conducted for this dissertation were spatial, but not specifically geospatial in nature. The most common tasks, those reported in the general analysis section, are all strictly spatial tasks in nature. As a result, we conclude that the findings of this dissertation in the analysis chapter (Chapter 10) and conclusion chapter (Chapter 11) can also be extrapolated to include generic spatial visualizations.

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