ABSTRACT

HUBER, DANIEL ERIC. Simple Motion in Glyph-Based Visualization. (Under the direction of Dr. Christopher G. Healey).

Visualizations provide many advantages over textual displays as a means to analyze and explore large sets of data. When analyzing data visually, users often want to perform two tasks: identify elements with specific values, and discriminate between elements with different values. Both of these tasks can be aided through the proper application of visual features in visualizations. Our objective is to study how two properties of simple motion, direction of motion and flicker, can be used to effectively aid the discrimination task in a visualization.

We present two user studies and an example of a practical application in the meteorological domain. Our user studies consist of visual search experiments in which viewers are asked to detect the presence or absence of a target group of elements within a background group as quickly and as accurately as possible. Direction of motion is tested by varying the angular difference between target and background motion and measuring mean viewer error rates and response times. In our study, viewers needed an angular separation of at least $30°$ in order to rapidly and accurately detect the presence of the target. Flicker is tested by varying the difference in flicker rate between the target and background for both coherent and noncoherent flicker. In our experiment, viewers were able to rapidly and accurately detect the presence of the target when target and background elements flickered coherently, regardless of the difference in rate of flicker. During the noncoherent flicker experiment, viewers were only able to accurately detect the presence of the target when the target or background flickered rapidly and there was at least a 240 ms difference between target and background cycle times. Finally, we show that

by using the results from our user studies in our weather data visualization, groups of similar elements are easily distinguishable.

Simple Motion in Glyph-Based Visualization

by

DANIEL E. HUBER

A thesis submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Department of
COMPUTER SCIENCE

Raleigh, North Carolina

2004

APPROVED BY:

H. S. Perr

Christopher G. Healey
Chair of Advisory Committee

BIOGRAPHY

Daniel Eric Huber was born on January 2, 1980 in Bristol, Pennsylvania to Walter and Sharon Huber. In 2002, he received a Bachelor of Science degree in Computer Science with a minor in Mathematics from Lafayette College, Easton, Pennsylvania. In the Fall of 2002, he entered the graduate program in Computer Science at North Carolina State University. Dan has accepted a job offer from Northrop Grumman Corporation where he will begin work after graduation.

ACKNOWLEDGMENTS

Several people helped me along the way in completing this thesis by giving thoughtful suggestions and guidance. Most importantly, they gave me the support needed to reach the finish line. My committee members, Dr. Christopher G. Healey, Dr. R. Michael Young, and Dr. Harry Perros, proved to be outstanding, especially my advisor and committee chair, Dr. Healey, who was a great source of knowledge about topics inside and out of this thesis.

Without the help of my peers I would have found the thesis-road bumpy and long. In the lab, I thank Brent, Laura, Amit, Sarat, and Reshma for giving me pointers and helping me with my presentation. It is much easier when there are people who have been there before and gone through it all. I especially thank Brent who answered so many of my questions and was a constant source of advice. Outside of the lab, my time at NC State would have been much more boring without the friendships of Joe and Sean. Thanks guys for making my time at NC State very enjoyable.

I also thank Kasia, whose love and affection I couldn't do without. She also listened to my presentation in those final hours and gave me much confidence.

Finally, I thank my parents and brothers who have given me support and encouragement throughout my life, and continue to be a great influence.

Contents

List of Figures

Chapter 1

Introduction

Computers have long been used to process and store large amounts of complex information as sets of numbers and strings. However, working with data in such a raw form is not always the most productive approach to analyzing a problem. Even if it were possible to read through the number of pages required to present data from a large data set, it is easy to miss potentially interesting phenomena. This is because our visual system is not optimized to process large amounts of text for trends or relationships between the different values. On the other hand, our ability to process, recognize and remember relationships within images is much stronger. As computers became cheaper, faster and capable of processing larger amounts of data, researchers have started to take advantage of the strengths in our visual system by developing methods to transform numerical and textual information into images displayed on a computer screen. This process is known as visualization.

Expressing numerical data visually is not exclusive to the computer and in fact goes back much further than the computer itself. As early as 1686, Edmund Halley created a world map that depicted the path of trade winds and the locations of monsoons. Halley drew strokes characterized by one end being noticeably thinner than the other. The strokes were drawn in patterns, which resemble vector fields, to show the direction of the winds (the wind came from the direction of the thin end on each stroke). Monsoons were represented by dense areas of alternating strokes [Tuf83].

Over time, visualizations have aided people in analyzing as well as discovering new patterns in complex information sets. Scientists in fields ranging from medicine to meteorology to civil engineering have all benefited from being able to explore data visually while performing tasks such as diagnosing patients or predicting future events [BA02, Tre99]. Researchers have found that visualization systems are also particularly useful for analyzing abstract data, for example, the wealth of information stored in databases, or network traffic patterns. [CAL+97, BP01].

There are two fundamental tasks users often want to perform when viewing data visually. First, they may want to easily discriminate between the values of two pieces of data. Said differently, a user will want to form mental groupings of similar pieces of data. Second, users will want to easily identify the value of a single data point or the difference between values of two or more data points. As it turns out, the discrimination task is often much easier than the identification task. This is because being able to identify the value of two pieces of data generally implies, as a necessary condition, the ability to discriminate between them.

With the goals of providing discriminability and identifiability, the designer of a visualization system must carefully address the issue of how raw data is represented by visual elements. The type, style, and placement of the elements will have a significant effect on a user's ability to perform the two fundamental tasks.

Today's computers can process and store enormous amounts of information. As a result, useful data sets often have a large number of elements as well as a high dimensionality, meaning each sample point encodes multiple attributes. Dealing with multi-dimensional data sets can be especially challenging. It is often difficult to display all the attributes associated with each element simultaneously. One approach for dealing with this situation uses simple visual elements called glyphs. A glyph is the building block of the visualization. A glyph possesses distinguishing visual characteristics such as shape, color, orientation and density. Each attribute of the data set controls one characteristic, or visual feature, of a glyph.

In order to harness the power of our low-level vision system during visualization, study in the field of cognitive psychology is required. In particular, results from visual perception experiments can be directly applied to the task of choosing effective visual features for a visualization. Image properties such as color, orientation, density, size, shape and motion have been determined to be processed by our vision system preattentively, meaning that we are able to quickly discern certain aspects of these features without the need for focused attention. In other words, the features often 'pop out' of the display, making them easily distinguishable. Using visual features that are processed preattentively can lead to visualizations that facilitate rapid and accurate discrimination and identification of information. Previous research in our lab has shown how color, texture and orientation can be used effectively in visualizations [HE98, HE99, HE96, Hea96].

This thesis explores the use of motion in visualizations. We chose to use motion as a visual feature because it possesses strong perceptual cues. Over the past twenty years, psychologists have supported this claim by reporting on how humans perceive motion. Simple linear motion has been found to be processed preattentively when elements are moving in sufficiently different directions [DD92]. Additionally, motion has been shown to effectively aid the process of grouping elements [Bra98]. These properties make motion an excellent candidate for use as a visual feature in visualizations.

Unfortunately, few experiments have determined appropriate values of motion to use in visualizations. We investigated how simple linear motion and flicker, or blinking, can be used effectively. For each type of motion, we wanted to know the conditions that make the feature ‘pop out’. To do this, we set up two visual search experiments, one for linear motion and one for flicker. In each setup, a sequence of search trials was presented to a viewer. Each trial consisted of a group of similar elements and potentially a smaller target group of dissimilar elements located within the larger group. Viewers were asked to determine as quickly and as accurately as possible whether or not a target group appeared within the larger group. We recorded accuracy and response time as a measure of viewer performance. After a short delay, the next trial was presented. Results from our study show how simple linear motion and flicker can be used in visualizations effectively.

Our first experiment explored how large an angular difference is needed to easily discriminate between two groups of elements moving linearly. In this case, the target elements differed from the background elements only in their direction of motion.

Our second experiment attempted to answer two questions: how large an interval is needed between the rate of flicker of two groups of elements in order to distinguish one from the other, and how does coherence of phase between individual elements within groups affect the ability to easily recognize a difference between groups? In these cases, the target elements differed from the background elements by rate of flicker, and possibly by the phase of their flicker pattern.

Finally, we created visualizations of weather data using linear motion and flicker as visual features. The application confirms that linear motion and flicker can be used to effectively discriminate between groups of elements with different attributes in a practical application domain.

The remaining chapters of this thesis are as follows. An overview of visualization is given in chapter 2, and motion in chapter 3. A description and analysis of the linear motion experiment is given in chapter 4 and of the flicker experiment in chapter 5. A sample visualization with motion is discussed in chapter 6. Concluding remarks and ideas for future work are then given in chapter 7.

Chapter 2

Visualization

2.1 What Is Visualization

In the simplest of terms, visualization is the process of transforming numerical and textual information into images. The images express the values, structure and relationships in data sets and allow exploration in a way that plain text cannot provide.

There are generally considered two categories of visualization, scientific and information. The major difference between the two types is that scientific visualizations display data that contain some inherent spatial property. Spatial locations for each data element must be computed in an information visualization. This is often done by simply mapping data attributes to each of the spatial axes (e.g., as is done for horizontal and vertical axes in a 2D graph). Both types of visualizations share many properties and as a result, techniques used in a scientific visualization can often be applied to an information visualization and vice versa.

Mathematically speaking, a visualization is a function, M, that maps a data set, D, composed of n sample points, or elements, $\{e_1 \ldots e_n\}$, into some visual representation, V.

$$M : D = \{e_1 \ldots e_n\} \rightarrow V$$

There are thus three phases in the creation of a visualization. First, the type of data set and elements to be analyzed must be chosen. Sources of data come from many different disciplines. This first phase drives the visualization because it strongly affects the decisions made during the second and third phases of creating a visualization. The second phase chooses a visual representation. Visual representations vary greatly from one application to the next. Consequently, creating and improving visual representations are often the focus of research in the visualization community. Common types of visual representations include scatterplots, volume visualizations, tree structures and glyphs. Lastly, the mapping, M, from data elements to visual representation must be chosen. Some visualization architectures help users determine an appropriate mapping. For example, one visualization system helps users choose an effective M by posing a sequence of questions to the user. The responses to the questions guide a visualization assistant to select perceptually optimal methods for converting a data set into a visualization [HSAE99].

Many data sets also have several dimensions, meaning each data element consists of two or more attribute values. This complicates matters further. A multi-dimensional data set contains a set of m attributes, $A = \{A_1 \ldots A_m\}$. Each dimension of the data set corresponds to some attribute A_j. Thus, each data element e_i is composed of m attribute values, $e_i = \{a_1 \ldots a_m\}$, where each a_j is the value of attribute A_j. An increase in dimensionality affects both the choice of visual representation and the choice of mapping from data elements to visual representation. These topics are addressed later in this chapter.

2.2 Foundations of Visualization

Visualization in scientific computing traces its roots back to a panel discussion in the 1980's where members expressed the need to apply graphics and image technologies to computational science. They stated a goal for visualization to "provide new scientific insight through visual methods." This goal was based on the observation that scientific discovery is the process of gaining insight through error. They concluded that "the most potential for visualization is the insight gained and mistakes understood by spotting visual anomalies while computing" [MDB87].

Today, several disciplines form the basis for developments in visualization. Within computer science alone there are a number of subfields involved including computer graphics, animation, computer vision, image processing and user interface design. Many of the improvements in the field have come about from other sciences as well. Medicine, meteorology, and economics are just some of the industries that push visualization further with their need to analyze large quantities of data.

Another critical area to the study of visualizations comes from cognitive psychology. Researchers in this field study how the human visual system 'sees' visual properties in the world around us. In the context of visualizations, cognitive psychologists are interested in how humans perceive visual imagery. Knowledge gained regarding this activity can lead to visualizations that express greater amounts of information more intuitively. Chapter three discusses the topic of visual perception in more detail.

2.3 Benefits of Visualization

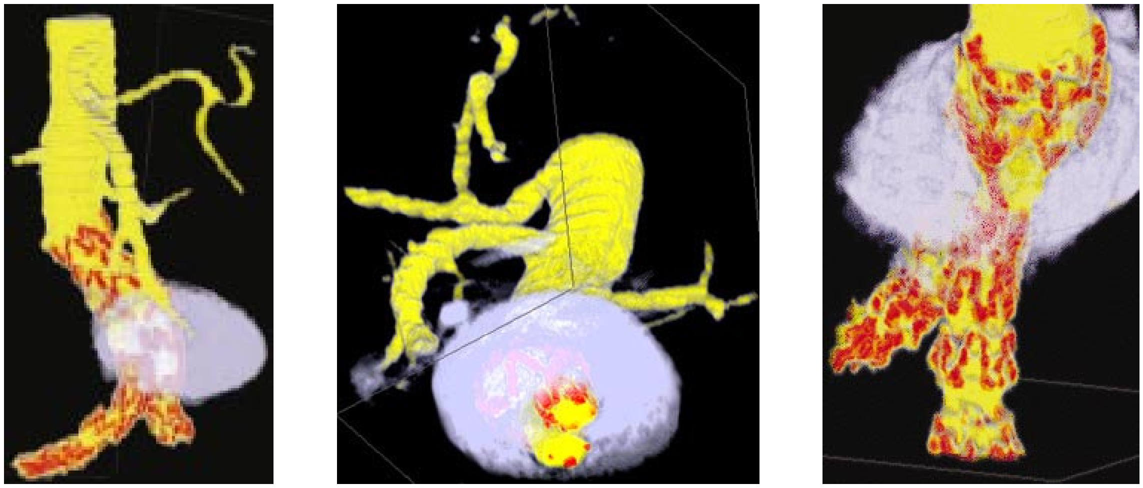
There are many reasons why one would want to examine data visually. A visual representation of data can provide a prompt qualitative overview without giving specific quantitative details. Having a general visual overview contained within a single display allows a user to make quick and accurate deductions because he or she is able to consume relevant high-level information all at once. Oftentimes only a cursory glance is required to form important conclusions.

When further analysis of a large data set is required, a visualization can help identify areas of interest for in-depth exploration. Dennis and Healey developed a navigation assistant that clusters potentially important data into spatially-coherent regions and facilitates investigation through an intelligent camera planner [DH02]. An effective user interface would also allow a user to manually navigate and select areas of interest, which triggers the display of a higher level of detail for the selected elements.

Visualizations are also a powerful means to enhance identification of structure, patterns, trends and other relationships between elements of a data set. Such tasks may not be as effortlessly performed without a visual representation. In fact, large data sets can easily overwhelm users, so much so that pertinent relationships are overlooked. Miller's work from cognitive psychology in 1956 implies that by taking advantage of humans' visual abilities a larger amount of information can be processed without overload [Mil]. Researchers have addressed this issue by creating methods to display as much information in as small a space as possible while still maintaining comprehensibility of all data attributes.

Yet another advantage visualizations provide is the ability to explore and discover new relationships within a data set. In 1854, an outbreak of cholera took the lives of several hundred Londoners. The source of the infectious disease was unknown until Dr. John Snow drew a map showing the locations of each death and the locations of eleven area water pumps. It became obvious that a centrally located water pump was contaminated [Tuf83]. In more recent times, visualization has provided a means to view and explore invisible natural phenomena. The atomic nucleus is so small that current photographic technology cannot capture its structure. However, an abundance of precise data exists to describe the nucleus' energy states. Cook et al. developed an application to visualize and interact with several theoretical models of the nucleus. The authors' goal was to provide a means for physicists to explore the atomic nucleus in ways that numerical data alone does not allow [CHY99]. Figure 2.1 shows a volume visualization of reconstructed CT (computed tomography) slices of an abdominal aortic aneurysm and the stents used to reinforce it.

Occasionally, the ability to manipulate data by hand visually is easier than making similar modifications through a text based interface. Some visualization architectures account for this by providing an interface to edit data. For example, Aiken et al. allow users to browse a visualization of a database and stop to make edits directly within the display [ACSW96].



(a) (b) (c)

Figure 2.1: An abdominal aortic aneurysm visualized with different colourmaps and viewing directions: (a) an aneurysm visualized using a perceptual colourmap; (b) a cut through the volume created with Volren's interactive clip planes, showing the cross-sectional area of the aneurysm and the two iliac arteries, and the location of tynes (metal hooks) in a stent used to reinforce the artery wall; (c) an orthogonal viewing direction, showing clearly the location of the tynes in the vertical iliac artery.

2.4 Visualization Design

There are a number of considerations that must be taken into account when designing a visualization architecture. To address these considerations, answering the question: what makes an effective visualization, is a good place to start. In his book, Edward Tufte describes several aspects of how to display quantitative information. Two techniques are directly relevant to our discussion on visualization. First, a display should show data accurately, without distorting meaning. Second, data should be displayed in a way that encourages comparisons between different elements [Tuf83]. Adhering to these guidelines is critical to the fundamental tasks of discriminability and identifiability.

Other design decisions should also be considered. In many cases, the decisions made should be strongly tied to specific application areas and implementation requirements. In his case study on operational weather forecasting, Treinish points out that using generic visualization techniques without regard for the users' goals can prove to be counterproductive. Instead, he suggests that a careful composition of visual elements to describe data such as temperature, wind speed, and precipitation will result in more effective visualizations [Tre99]. While it is generally not cost effective to develop specific visualization applications for every possible type of data set, Treinish's work suggests the importance of a user-guided method to specify visualization parameters. Robertson and De Ferrari describe a visualization reference model that lets users specify visual directives, such as, "show variable X using representation R," and interpretation aims, such as, "show local trends for variable Y and its correlation with variable Z" [RDF94]. Allowing the user to configure the visualization to suit his or her needs can improve data exploration and knowledge discovery by making the discriminability and identifiability tasks easier. In an effort to aid the user in configuring a visualization, mixed-initiative algorithms have been used to guide the user through a series of questions [KFL91, Koc94, HSAE99].

2.5 Multi-Dimensional Visualization

Recall that a multi-dimensional data set is one where each data element is comprised of more than one attribute value. For example, in a weather data set, each sample point might encode location, temperature, amount of precipitation, and wind speed. The techniques for visualizing multi-dimensional data have received considerable attention in the visualization community. Some researchers focus on the development of novel visual representations to represent such data, while others concentrate on improving how data is mapped to specific visual representations. Both of these areas of research address the issue posed by Grinstein: how can we improve the consumption of large quantities of data? [GLI98]

The difficulty in visualizing multi-dimensional data arises from the fact that most displays are two-dimensional, for example, a computer screen or a sheet of paper. Therefore, methods are needed to compress multi-dimensional data into some representation that can be displayed in a two-dimensional space. In the case of computers, it is often sufficient to transform data into three-dimensional space and then let traditional computer graphics techniques project the representation onto a screen. Clearly, each dimension adds an additional challenge to identifying attribute values of data elements and discriminating between them. Consequently, several types of visual representations have been developed to cope with visualizing large, multi-dimensional data sets.

Pixel based Visual Representations

One method for displaying large amounts of data in a small space is based on pixels as the underlying representation. Pixels were chosen because they are the smallest elements that can be displayed on a computer screen, and therefore, mapping one attribute value to one pixel allows the largest amount of information to be viewed at once. Keim and Kriegel designed a visualization system where each attribute value of a data element controls the color of a pixel. The pixels are arranged in a spiral about some user defined reference point, where a pixel's position along the spiral is determined by how similar the corresponding data point is to the reference point. Separate dimensions are either viewed in separate windows or by grouping the pixels comprising one data element along the spiral [KK95].

Because the attributes of a sample point are either spread across multiple views or arbitrarily arranged together, it can be difficult to ascertain the values of each attribute of a single data point. It also makes comparing data elements difficult.

Glyph based Visual Representations

A category of multi-dimensional visualizations that can provide a better coupling of attributes to sample points uses simple visual elements called glyphs to represent data elements. Glyphs are composed of several different visual features and are thus able to encode several dimensions of information in a single object. Glyphs come in many different varieties, some of which are described here.

Star plots use a point to represent each data element and lines protruding from each point to represent attribute values. The length of each line is determined by the value of the corresponding attribute [Spe99].

A slightly more amusing type of glyph is called a Chernoff face. These visual elements take advantage of a human's ability to differentiate between other human faces. Each glyph is a stylized drawing of a human face where values of attributes are encoded by the size, shape and separation of different facial features [Che73].

Another glyph-based visualization that harnesses humans' perceptual abilities uses texture elements as the building blocks of a visualization. Healey and Enns describe a system where data points are represented by perceptual texture elements, or pexels. The pexels are placed

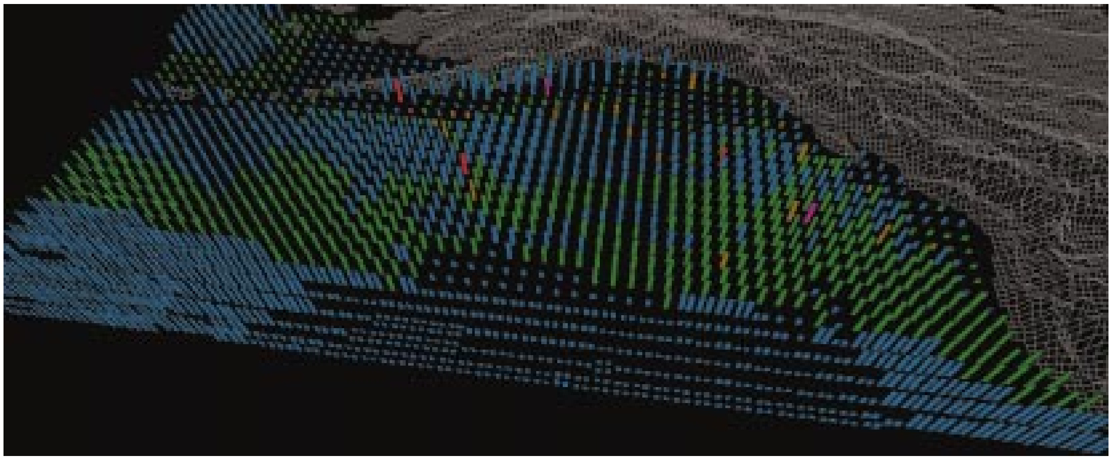


Figure 2.2: Visualization of the oceanography datasets, color used to represent plankton density (blue, green, brown, red, and purple represent lowest to highest densities), height used to represent current strength, texture density used to represent SST: February, 1956.

on a gridded surface with each cell containing one data element. Each pexel can be identified by a combination of its visual features, e.g. color, luminance, orientation, height, density and regularity. Each attribute of a data set controls one visual feature, for example, in a weather data set, wind speed might be mapped to the height of a pexel [HE98, HE99, IFG$^+$98, Hea96, HE96].

Figure 2.2 shows a data frame from an oceanography dataset representing seasonal ocean conditions for February, 1956. These datasets are analyzed in the context of simulations of salmon migration patterns, which are used to try to identify where in the open ocean salmon feed and grow during the year. Color shows the variation in plankton densities (blue, green, brown, red, and purple for low to high densities). Height shows current strength (taller for stronger). Density shows sea-surface temperature (denser for higher). This mapping allow the oceanographers to track current strengths and SSTs. In February, most plankton densities are less than 28 g/m^3 (*i.e.,* blue and green strips). Currents are low in the north-central Pacific;

a region of weak currents also sits off the south coast of Alaska. Most of the ocean is cold (sparse pexels), although a region of higher temperatures can easily be seen as dense pexels in the south.

A disadvantage of glyph-based visualizations is that there are normally fewer data elements per display, although there is not necessarily less total data shown because each glyph can encode multiple data values. Fortunately, the results of the pexel-based visualizations show that taking advantage of the strengths of the low-level human vision system can help users analyze large multi-dimensional displays quickly and correctly with little effort. Thus, we need some way to map attributes of a data set to visual features based on visual perception, the topic of the next chapter of this thesis.

Chapter 3

Motion

3.1 Visual Perception Overview

In the context of statistical displays, Tufte describes graphical excellence as being the communication of complex ideas in the least amount of space with precision, clarity, and efficiency [Tuf83]. The application of theories in visual perception to visualization is one way to help achieve graphical excellence.

Studies in visual perception attempt to determine how humans analyze images. Contributors from cognitive psychology, psychophysics, computer science and other fields continue to provide a great deal of information on this topic. We are concerned with studies on the perceptual strengths and weaknesses of various visual features, in particular, simple motion. We want to know how motion can be used to facilitate accurate and efficient detection and grouping of visual elements, in a manner similar to previous research on the perceptual strengths of color and texture in visualization design [IFG$^+$98, Hea96, HE98, HE99].

Perceptual efficiency is critical to an effective information display. By using visual features that can be rapidly identified, users can process data quickly and easily. Typically, a visual feature is considered perceptually efficient if it can be detected in less than 200-250 milliseconds. Determining the efficiency and accuracy of a particular perceptual task can be difficult. One popular strategy uses visual search experiments. In a visual search experiment a viewer views a sequence of images, and for each image the viewer is asked to determine if some identifying characteristic is present or absent. For example, a viewer may be asked to determine if a red circle is present in a field of red squares and blue circles. The response time and accuracy of each response is recorded. These values can be analyzed to measure a viewer's performance during the search task. Details of our visual search experiments with linear motion and flicker are given in the next two chapters.

The ability to mentally group elements by visual feature is an important task in visualization. Treisman, Driver and Nakayama are among many who found that perceptual groups in a single display can be searched independently [TG80, Tre82, DD92, NS86]. McLeod et al. also showed that even if elements belonging to one perceptual group are scattered among other elements, search can still be restricted to the perceptual group [MDC88]. These are some of the strengths motion can offer as a visual feature.

3.2 Properties of Motion

Like color, texture and shape, motion is considered a fundamental sense. Consequently, the ability to perceive motion provides many benefits to humans. Cues given by motion of objects can help encode depth and relative distances of objects. Perception of motion is also essential in anticipating the time to collision of moving objects. Most important to this thesis, motion cues can also aid in image segmentation, e.g. the detection and grouping tasks mentioned previously [Nak85].

Computers can give the impression of continuous motion through a perceptual illusion known as the phi phenomenon. Simulated motion occurs when a sequence of static images containing an object displaced by small increments are displayed in rapid succession. The brain fuses the images together and motion is perceived. The rate at which successive images need to be presented in order to perceive motion is known as the critical flicker frequency. The critical flicker frequency varies depending on color, brightness, and size of objects to be displayed but is generally around 60 images per second.

Motion of an object can range from simple to complex. Some motion types are anchored about a specific point. Example anchored motions include rotation, oscillation, flicker, and deformation. Other motion types are not constrained in this way. These motions include simple linear motion and motion of an object along a vector field. We chose to test simple linear motion and flicker in our visualizations. As a result, we studied how direction of motion and flicker can be used in a perceptually efficient manner.

3.2.1 Direction of Motion

Motion of an object as it changes position is characterized by two quantities, direction and speed. Matthews and Qian report that the senses in the brain that detect differences in direction and differences in speed of two objects are at least partially independent. This implies that the threshold for detecting small differences in direction may be different than the threshold for detecting small differences in speed [MLGQ99]. Speed of an object, however, does influence the time it takes to detect a difference in direction of moving stimuli. In visual search experiments speed is often measured in degrees per second, which is the rate at which the visual angle between the center of focus and an object changes. De Bruyn and Orban reported on the relation of direction discrimination to speed measured with random dot patterns. They found that discrimination improved as speed increased to approximately 4 degrees per second. That threshold remained constant up to a speed of approximately 128 degrees per second. For speeds greater than 128 degrees per second, the ability to discriminate direction differences deteriorated [DBO88].

Differences in the direction of motion of glyphs provide cues to help identify individual elements that differ from the field. Nothdurft reported on the ability to discriminate direction of an incoherently moving target dot in a field of coherently moving background dots. The direction of each background dot was allowed to vary slightly from the direction of its neighbors. Nothdurft found that as the maximum allowable variation between background dots increased (i.e. the background dots lost their coherent motion pattern), the difference in direction needed to detect the target dot increased even more rapidly. When the maximum allowable variation between background dots was 60 degrees, the target dot was effectively hidden amongst the background and could no longer be accurately detected [Not93].

Perceptual grouping tasks are also aided through proper use of direction of motion. In multi-dimensional visualizations, grouping tasks can be complicated by visual features used in conjunction. In addition to identifying preattentive features, visual search experiments can help identify features that are perceptually efficient when used in conjunction. For example, detecting a red circle in a group of blue circles or a group of red squares is easy. However, detecting a red circle among a group of blue circles and red squares is more difficult. See Figure 3.1 for such an example of conjunction search versus preattentive search. Nakayama and Silverman showed that when sets of elements move coherently, e.g. in the same direction, viewers can easily form mental groups from each set and can search the groups independently, without interference between groups [NS86]. Driver et al. also showed that linear motion, in the form of oscillation, can be used to separate elements into distinct visual groups. However, they found that perceptually efficient motion is only produced when elements in each group oscillate with the same phase. For example, finding a horizontally moving X among a field of vertically moving X's and horizontally moving O's is easy when horizontal elements move together and vertical elements move together. When elements within each group move out of phase, it is much more difficult to find the horizontally moving X [DD92].

Average luminance levels also affect the ability to segregate texture by motion. Takeuchi et al. found that the minimum amount of time to detect a difference in the direction of two moving textures increases as luminance decreases [TYDV04]. Many perceptual tasks are easier when the stimulus is presented near the focus of attention. However, Takeuchi et al. also found that in low luminance conditions, detection of a difference in motion in the periphery is easier than detection near the fovea, or center of attention [TYDV04].

Research suggests that detection of difference in motion between elements is influenced by a perception of a global motion pattern in addition to perceived differences in local motion. Bravo created an experiment that essentially 'windowed' groups of dots moving in the same direction within each window. The windows separated groups so that perceived differences in direction were not due to edges formed by local velocity differences. Viewers were asked to identify the window containing dots moving in a direction incoherent from the pattern formed by motion in the other windows. Bravo concluded that moving stimuli can be segregated at a global level, without the need for perceived differences in direction of motion at the boundaries [Bra98].

The performance of many perceptual tasks can be improved through repeated practice. Ball and Sekuler reported on the ability to learn direction of motion discrimination. Viewers were trained every day for approximately 30 minutes. Results showed that learning was specific to an area within 45 degrees of the trained direction. Effects of training lasted at least 10 weeks [BS87]. Matthews et al. produced a follow-up report that showed training on direction discrimination transferred to orientation discrimination. However, training on orientation did not transfer to direction learning [MLGQ99].

3.2.2 Flicker

We are interested in the properties of perceivable intermittent stimulation produced by flickering glyphs. The rate at which flicker occurs in order to perceive a distinct on-off pattern must be below the critical flicker frequency (CFF). The CFF is influenced by many variables of the stimulus as well as other human factors, such as age. The luminance value of a stimulus strongly affects the minimum frequency at which image fusion occurs. Graham reports that at high luminance levels, CFF is approximately 60 cycles per second (cps). However, under low luminance conditions, CFF is reduced to approximately 15 cps [Gra65]. Additionally, the effects of luminance on the CFF are different when the flickering stimulus is presented in the periphery versus in the fovea. Under high luminance, the CFF is greater for stimulus in the fovea than in the periphery. Conversely, with low luminance, the CFF is lower for stimulus in the fovea than in the periphery [Bro65].

Discrimination of flicker rate is an important task if flicker is to be used in visualization. Brown discusses several factors that influence our sensitivity to flicker rate discrimination. Luminance affects rate discrimination, in addition to its impact on CFF. Specifically, as luminance increases, the perceived rate of flicker decreases [Bro65]. Brown also discusses the differential frequency threshold, $\Delta F/F$, which is a measure of the smallest detectable change in flicker rate ΔF for a given baseline rate F. Data was recorded for flicker rates between 8.4 cps and 51 cps. Over this range, $\Delta F/F$ was found to vary from 0.02 to 0.05, meaning that the rates of flicker must differ by about 2-5% in order to produce a distinguishable a difference. It was shown that a flicker rate of 22.5 cps required the largest ΔF to produce a visible difference [Bro65]. Eccentricity, the angle between a viewer's center of view and a stimulus, also affects the differential frequency threshold. ΔF is generally higher for a stimulus presented in the periphery than in the fovea [Bro65].

3.3 Motion in Visualization

Motion has been used in visualizations for a variety of purposes. Wright discussed several ways to use motion to enhance and improve visualizations of capital market data. Animation was used to let users move around data and zoom in on areas of interest. He also showed that motion can be effectively used to replay changes in data over time. Using motion for play back purpose increased the amount of Federal bond market information displayed by two orders of magnitude when compared to a traditional quote screen display. Wright also used motion of a curve to communicate projected profits and losses [Wri95].

Motion can also be effective at attracting attention in a visualization. Bartram et al. used simple motion of icons as an alert to users engaged in some visually demanding task. They found that motion as a notification mechanism is better than a static change of color or shape, especially when the notification icon appears in the user's periphery. Less than 2% of alerts cued by motion were missed versus 6% of alerts in the center of attention and 25% of alerts in the periphery cued by color. The authors also compared the distraction level of motion cues. They found anchored motions, e.g. flicker and rotation, to be less distracting than traveling motions [BWC01b].

Bartram et al. also found that different motion patterns are effective at grouping dissimilar, spatially dispersed glyphs. For example, glyphs with different colors and shapes that moved in a coherent circular motion pattern were efficiently separated from glyphs that oscillated. They also found that two groups of oscillating glyphs could be discriminated from one another most easily if their directions were separated by at least 16 degrees if the two directions came from two different quadrants (i.e. the two motions straddled either the x- or y-axis) [BWC01a].

Jesse and Strothotte use simple motion similar to Batram's. They use three types of motion, oscillation, rotation, and distortion, in their glyph-based visualizations to convey meaning to the user. It was shown that moving a glyph, or small subset of glyphs, among a group of static glyphs effectively brings the moving glyphs to attention. In this way, motion is used as a cue for spotting interesting data [JS01].

Motion is also effective at providing a general overview of trends in data. Kerlick used motion associated with specific shapes of glyphs to communicate information to users. For example, arrow and dart shaped glyphs moved along the path of a vector field to show the gradients in the data, while a spherical glyph was deformed to an ellipsoid according to the values of some tensor field [Ker90].

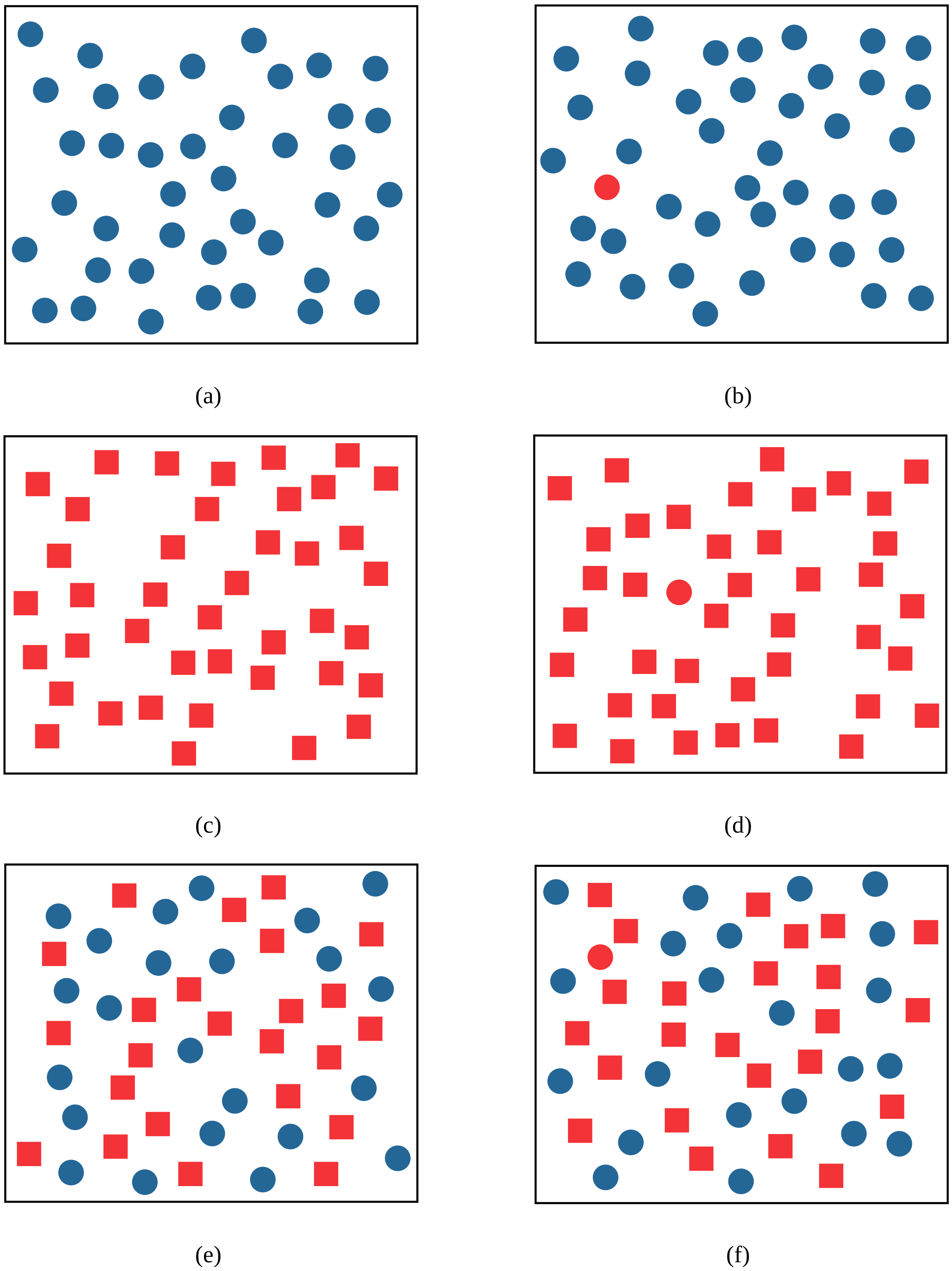


Figure 3.1: Examples of visual searches for color, shape and a conjunction of the two: (a) and (b) show that a search for a red circle among blue circles is rapid and accurate. (c) and (d) show that a search for a red circle among red squares is rapid and accurate. (e) and (f) show that a conjunction search for a red circle among blue circles and red squares is significantly more difficult; target is absent in (e), present in (f).

Chapter 4

Direction Experiment

Our direction of motion experiment was similar to some of the visual search experiments described in the preceding chapter. Viewers were asked to rapidly detect if a group of target elements was moving in a direction different than the background elements. Elements differed only by direction of motion. Based on the research reported in the previous chapter, we hypothesized that direction of motion could be used in a visualization to help discriminate between groups of elements with similar values.

4.1 Methods

4.1.1 Design

The stimuli were presented in a 20×20 grid of square cells inside a window with a black background. Boundaries between cells were not visible. Each cell contained a single moving *pexel* (perceptual texture element) in the shape of a yellow square, with area roughly equal to

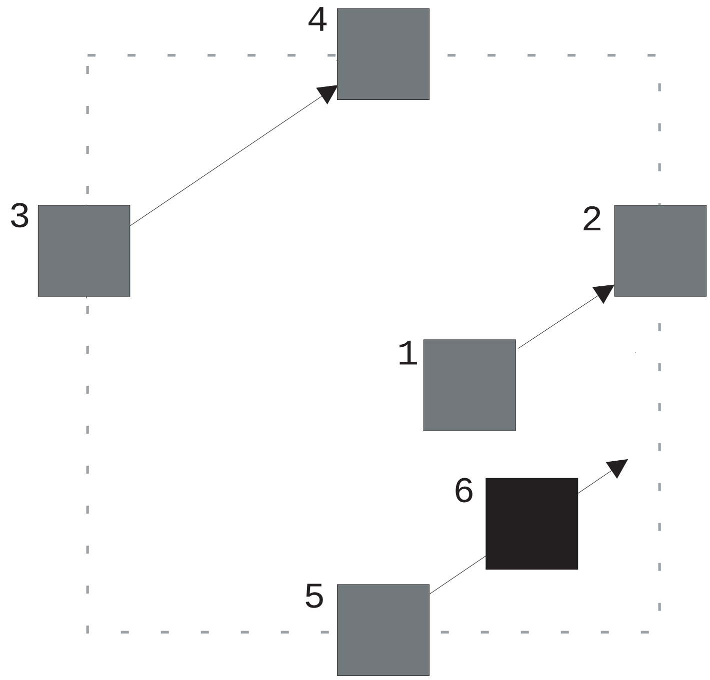
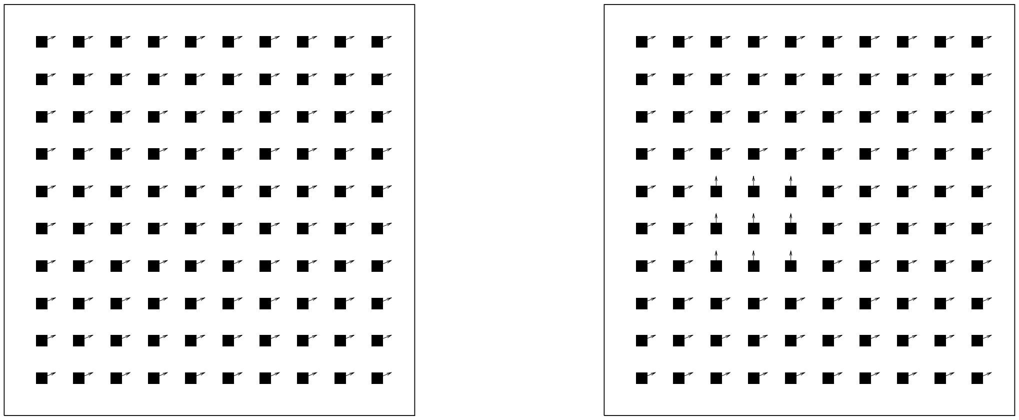


Figure 4.1: Example of pexel movement within a cell. The pexel moves in the direction of the arrows. Starting at (1), the pexel moves to (2), which is at the edge of a cell. The pexel then 'jumps' to (3), where it continues on to (4). (4) is also at the edge of the cell, so the pexel reappears at (5) and continues on to (6).

one-tenth of the area of a cell. The motion of a pexel was defined by its direction, d, and speed, s. When a pexel reached the edge of a cell it wrapped back around to the other side of the cell. See Figure 4.1 for an example of this behavior.

Direction of motion was constrained between $0°$ and $90°$ counter-clockwise from horizontal, i.e. pexels moved up, right, or up and to the right. The speeds of all pexels were identical and constant throughout the experiment. The starting offsets within each cell of every pexel were also identical.

During some trials, a 3 $\times$ 3 target patch of pexels was present within the field of background pexels. The target patch moved in the direction d_T whereas the background pexels moved in



(a) (b)

Figure 4.2: An example of two experiment displays on a 10×10 grid. The vectors extending from each pexel indicate the direction of motion. (a) no target is present; (b) a target with lower left corner in the third column and fourth row is present.

the direction d_B. When the target patch was present, d_T and d_B were never equal. Figure 4.2 shows example target-absent and target-present trials on a 10×10 grid of pexels.

Boundary Between Target and Background Pexels

When adjacent pexels had equal values for d and s, with the same relative starting offset, the impression of a continuous stream of pexels was created. All pexels reached the edge of their cells and 'jumped' back to the other side simultaneously. The space left empty by one pexel was filled by an adjacent pexel reappearing in its place. Thus, there was no evidence of a boundary between pexels.

However, when a target patch was present, a discontinuity at the boundary between background and target was formed by the difference in d_T and d_B. There were several ways to handle the transition between background and target patches. One solution was to do nothing.

Unfortunately, doing nothing produced a noticeable popping when pexels reached the edge of a cell. Entire pexels were removed and redrawn at new locations when their centers passed over cell boundaries. This caused the pexels within the target patch to appear to jump around instead of flow continuously. With such a large distraction it was difficult to determine if viewers would notice a difference in direction or the popping effect first.

A second solution was to gradually fade-out pexels as they approached the edge of a cell and fade-in pexels as they moved away from an edge. Unfortunately, the changes in luminance also created a distraction.

A third solution was to create a stencil around the target cells. A stencil can be thought of as a sheet of paper with a hole cut out. When elements pass under the stencil, only those portions that are underneath the hole are visible. Our stencil masks out background pexels extending into the target area as well as target pexels extending into the background area. This created the effect of pexels gradually disappearing from view. In order to make pexels gradually reappear on the other side of their cells as they disappeared, multiple pexels had to be drawn in each cell for some duration. By making pexels appear and disappear gradually, no jumping or change of luminance distractions were noticeable. We used a stencil around the target cells in our experiment.

4.1.2 Procedure

Viewers sat in front of an LCD screen at a comfortable viewing distance. Each viewer was presented with 540 trials in random order. In half of the trials, the target patch was present. Possible values for d_T and d_B were 0°, 10°, 20°, 30°, 40°, 50°, 60°, 70°, 80°, and 90°. Among the 270 trials with the target present, every combination of d_T and d_B, with $d_T \neq d_B$, was presented three times. The target patch was randomly located within the grid and at least one row and one column away from the edge of the grid.

For each trial, a viewer was asked to identify whether or not he or she saw a target group of pexels moving in a direction different than the background field of moving pexels. If the viewer perceived a target patch he or she pressed a key to indicate 'present'. If no target patch was seen, the viewer pressed a different key to indicate 'absent'. The viewer was asked to respond as quickly and accurately as possible. Response time and correctness of each trial were recorded. A one second delay occurred between the time a viewer indicated the presence or absence of a target and the time the next trial began. During the delay, feedback was given to the viewer in the form of a green plus sign for a correct response and a red minus sign for an incorrect response. After every 135 trials the viewer was given an opportunity to take a break for as long as needed.

Each viewer practiced on 36 trials immediately prior to completing the experiment. 18 practice trials contained a target; the other 18 did not. Among the practice trials with the target present, each magnitude of difference in direction that would be present during the experiment was presented twice.

4.1.3 Viewers

Ten viewers participated in the experiment. Some of the viewers were familiar with visual search experiments, while others did not have any previous experience. All viewers had normal or corrected-to-normal vision.

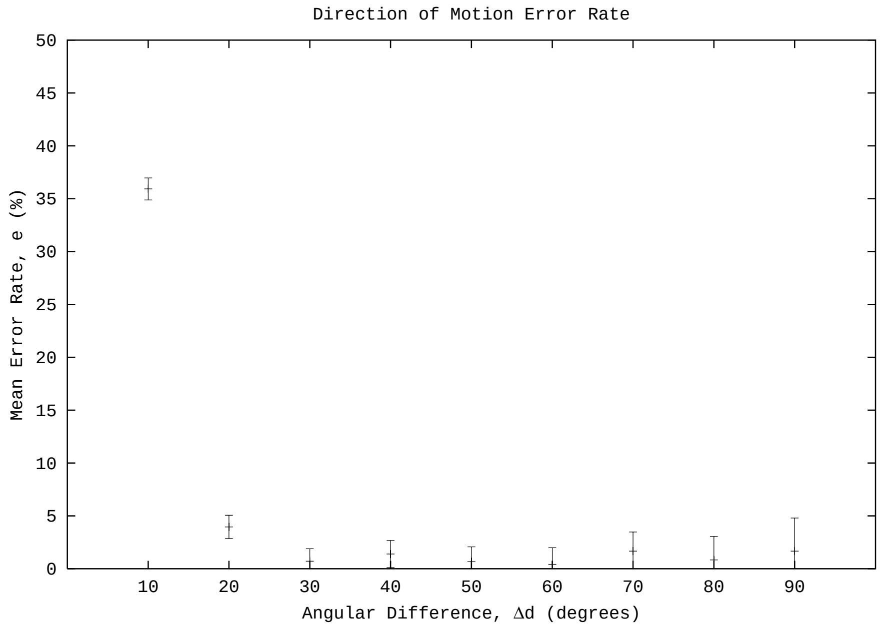


Figure 4.3: Mean error rates, $\overline{e}$, with error bars are plotted against angular difference, Δd, for the direction experiment. Error bars represent ± 1 standard error.

4.2 Results and Discussion

Performance was measured by mean viewer error rates, $\overline{e}$, and response times, $\overline{rt}$. Figure 4.3 shows $\overline{e}$ for each difference between d_T and d_B. At an angular difference $\Delta d = 10°$, viewers responded correctly on only 64% of trials. An increase to $\Delta d = 20°$ increased accuracy to 96%. With $\Delta d \geq 30°$ viewers responded correctly on more than 98% of trials. An analysis of variance (ANOVA) on the data shows that the magnitude of Δd had a significant impact on the accuracy at which viewers could rapidly discriminate between two groups of elements moving in different directions ($F = 108.8$, $p < 0.0001$).

Figure 4.4 shows $\overline{rt}$ for each Δd. As Δd increased, $\overline{rt}$ decreased until $\Delta d = 40°$ where response time leveled off to between 750 and 800 ms. A $\Delta d \leq 20°$ produced $\overline{rt}$ greater

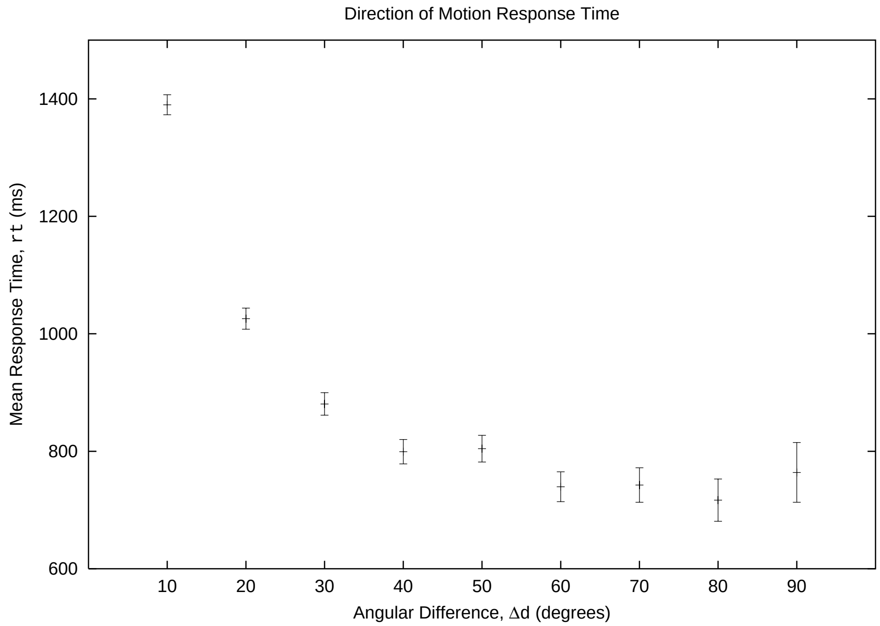


Figure 4.4: Mean response times, $\overline{rt}$, with error bars are plotted against angular difference, Δd, for the direction experiment. Error bars represent ± 1 standard error.

than 1 second. An ANOVA on the response time data shows that the magnitude of Δd was a significant factor in the time it took viewers to respond during the discrimination task ($F = 121.3$, $p < 0.0001$).

The results suggest that a target patch of moving pexels can be rapidly and accurately detected within a field of moving pexels when $\Delta d \geq 30°$. This confirms research presented earlier that linear motion can be used to segregate groups of elements effectively. We also found that viewers did not increase in accuracy or achieve faster response times as they progressed through the sequence of trials. Furthermore, when $\Delta d \geq 30°$, rapid and accurate detection is possible regardless of the specific background direction.

Chapter 5

Flicker Experiment

The design of our flicker experiment was similar to our direction of motion experiment. Viewers were asked to rapidly detect the presence or absence of a group of target elements flickering at a rate different than the background elements. In half of the experiment, elements differed only by flicker frequency. In the other half, elements differed by flicker frequency and phase. As with direction of motion, we hypothesized that flicker could be used in a visualization to help discriminate between groups of elements with similar values.

5.1 Methods

5.1.1 Design

The stimuli were presented as a 20×20 grid of yellow square pexels. Each pexel flickered on and off with frequency f in cycles per second (e.g. if the target is visible for 100 ms and invisible for 100 ms, then $f = 5$ cps). The duration of 'on' and 'off' stages were always equal.

During an ‘on’ stage the pexel was completely visible, and during an ‘off’ stage the pexel was completely invisible. T is the absolute duration (in milliseconds) of one cycle (e.g., $T = 200$ ms in the previous example).

The experiment was comprised of two sub-experiments, coherent flicker and noncoherent flicker. In the coherent flicker sub-experiment, all background pexels flickered with an identical frequency and a zero phase (i.e. all pexels blinked on and off at the same time). During the noncoherent flicker sub-experiment, all background pexels flickered with an identical frequency but random phases (i.e. all pexels blinked at the same rate, but not necessarily on and off together).

During some trials a 3×3 target patch of pexels was present. The target pexels flickered at a frequency f_T whereas the background pexels flickered at a frequency f_B. It was always the case that $f_T \neq f_B$. In the coherent sub-experiment, target pexels also had a zero phase. In the noncoherent sub-experiment, target pexels had random phases.

5.1.2 Procedure

Viewers sat in front of an LCD screen at a comfortable viewing distance. Half of the viewers were presented with the coherent sub-experiment first, while the others were presented with the noncoherent sub-experiment first. The procedures for both sub-experiments were the same. During each sub-experiment, each viewer was presented with 192 trials in random order. In half of the trials the target patch was present. The target was randomly located within the grid and at least one row and one column away from the edge of the grid. The magnitude of the difference between between target and background periods was one of 4 values: $\Delta T = 120$

ms (8.33 Hz), $\Delta T = 240$ ms (4.17 Hz), $\Delta T = 360$ ms (2.78 Hz), or $\Delta T = 480$ ms (2.08 Hz). Among the 96 trials with the target present, each ΔT was presented 24 times. The possible flicker rates of the target varied based on the ΔT being presented. With a target period T_T measured in milliseconds, for $\Delta T = 120$ ms, $T_T \in \{120, 240, 360, 480\}$; for $\Delta T = 240$ ms, $T_T \in \{240, 360, 480, 600\}$; for $\Delta T = 360$ ms, $T_T \in \{360, 480, 600, 720\}$; for $\Delta T = 480$ ms, $T_T \in \{480, 600, 720, 840\}$. The background pexels flickered with a period $T_B = T_T \pm \Delta T$, except where $T_T = \Delta T$, in which case $T_B = T_T + \Delta T$.

For each trial, a viewer was asked to identify whether or not he or she saw a group of pexels flickering at a rate different than the background pexels. The pexels continued to flicker until the viewer pressed a key to indicate 'present' if the target was seen or another key to indicate 'absent' if it was not. The viewer was asked to respond as quickly and as accurately as possible. Responses times and accuracy were recorded for each trial. A one second delay occurred between the time the viewer indicated the presence or absence of a target and the time the next trial began. During the delay, feedback was given to the viewer in the form of a green plus sign for a correct response and a red minus sign for an incorrect response. After every 48 trials the viewer was given an opportunity to take a break for as long as needed.

Immediately prior to completing each sub-experiment, the viewer practiced on 32 trials. 16 practice trials contained a target; the other 16 did not. Among the practice trials with the target present, each magnitude of difference in flicker rate that would be used during the experiment was presented four times.

5.1.3 Viewers

Eight viewers participated in the experiment. All viewers participated previously in the direction experiment described in the preceding chapter. All viewers had normal or corrected-to-normal vision.

5.2 Results and Discussion

Viewer performance was measured by mean error rates, $\overline{e}$, and mean number of visibility changes, $\overline{vc}$, that occurred before a response was made. $\overline{vc}$ tells us how many times the target or background switched on and off before the viewer responded. $\overline{vc}$ was calculated using the faster flicker rate between target and background, $T_{base} = min(T_T, T_B)$. Given a response time rt and a period T_{base}, the number of visibility changes vc for a single trial was:

$$vc = \lfloor 2\frac{rt}{T_{base}} \rfloor$$

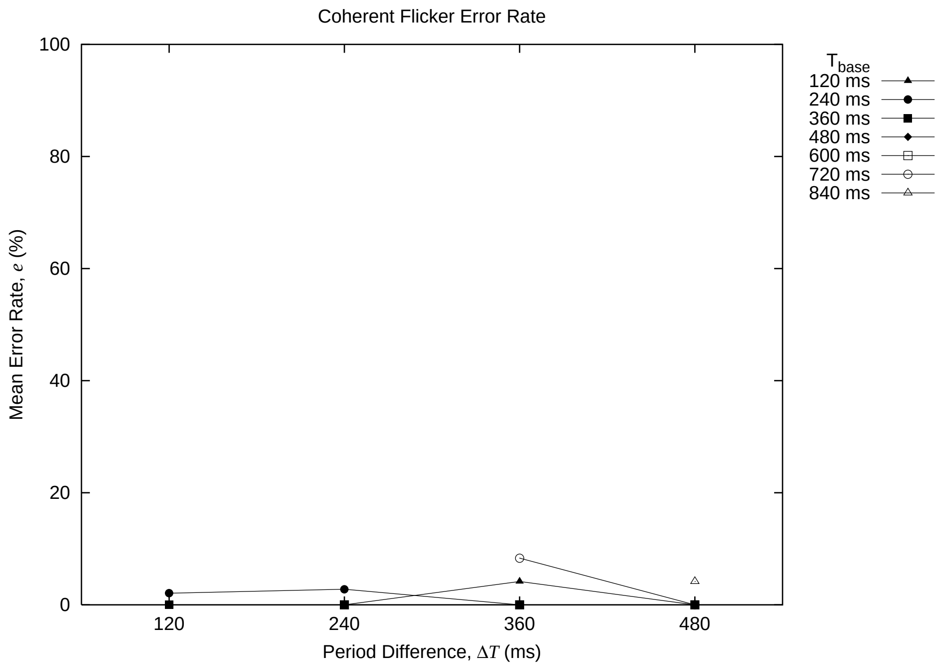
An important point to note about vc is that it depends on the minimum of the target and background periods. Therefore, we plotted $\overline{e}$ and $\overline{vc}$ versus ΔT for trials with the same T_{base}.

Figure 5.1 shows $\overline{e}$ for each combination of ΔT and T_{base} for both the coherent (Figure 5.1(a)) and noncoherent (Figure 5.1(b)) sub-experiments. Clearly, viewers were more accurate at detecting the presence of the target when all pexels flickered coherently. Viewers achieved near perfect accuracy regardless of T_{base} or ΔT. ΔT had no significant impact in $\overline{e}$ for every T_{base} ($p > 0.05$ for every T_{base}). When pexels flickered noncoherently, viewers responded incorrectly on more than 50% of trials for most T_{base}. Only for $T_{base} = 120$ ms did viewers respond correctly on more than half of trials for every ΔT (i.e., for rapidly flickering backgrounds or targets). In this case, when $\Delta T \geq 240$ ms viewers responded with near perfect accuracy. ΔT only had a significant impact on $\overline{e}$ for $T_{base} = 120$ ms ($p < 0.0001$). These results suggest that when $T_{base} = 120$ ms and pexels flickered noncoherently, viewers needed $\Delta T \geq 240$ in order to accurately detect the presence of a target.

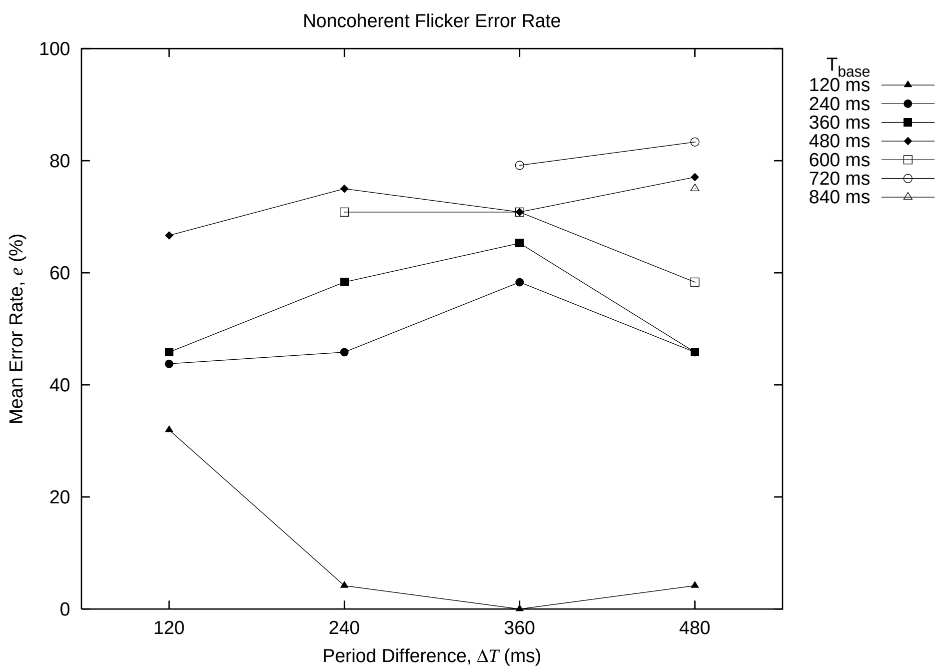
Figure 5.2 shows $\overline{vc}$ for each combination of ΔT and T_{base} for both the coherent (Figure 5.2(a)) and noncoherent (Figure 5.2(b)) sub-experiments. Again, viewers performed better when pexels flickered coherently. During coherent flicker $\overline{vc}$ was in the range 10-12 when $T_{base} = 120$ ms, and in the range 2-6 when $T_{base} \geq 240$ ms. With noncoherent flicker, $\overline{vc}$ was in the range 25-48 when $T_{base} = 120$ ms, and in the range 10-35 when $T_{base} \geq 240$ ms.

Furthermore, when pexels flickered coherently, $\overline{vc}$ did not vary significantly with different ΔT across T_{base}. ΔT only had a significant impact on $\overline{vc}$ for $T_{base} = 360$, but the absolute difference in $\overline{vc}$ in this case was only 1.25. With noncoherent flicker, $\overline{vc}$ did not vary significantly across ΔT. However, $\overline{vc}$ differs over ΔT for each T_{base} by more than 5 for $T_{base} \leq 360$. This suggests that viewers eventually 'gave up' and guessed whether the target was present or not.

The results of this experiment show that a target patch of flickering pexels can be detected rapidly and accurately regardless of the difference in flicker rate if the target and background pexels flicker coherently. No significant difference was found between viewers who completed the coherent sub-experiment first versus viewers who completed the noncoherent sub-experiment first. Additionally, based on results from our direction experiment, we assume that viewers did not increase performance in later trials based on early trials.

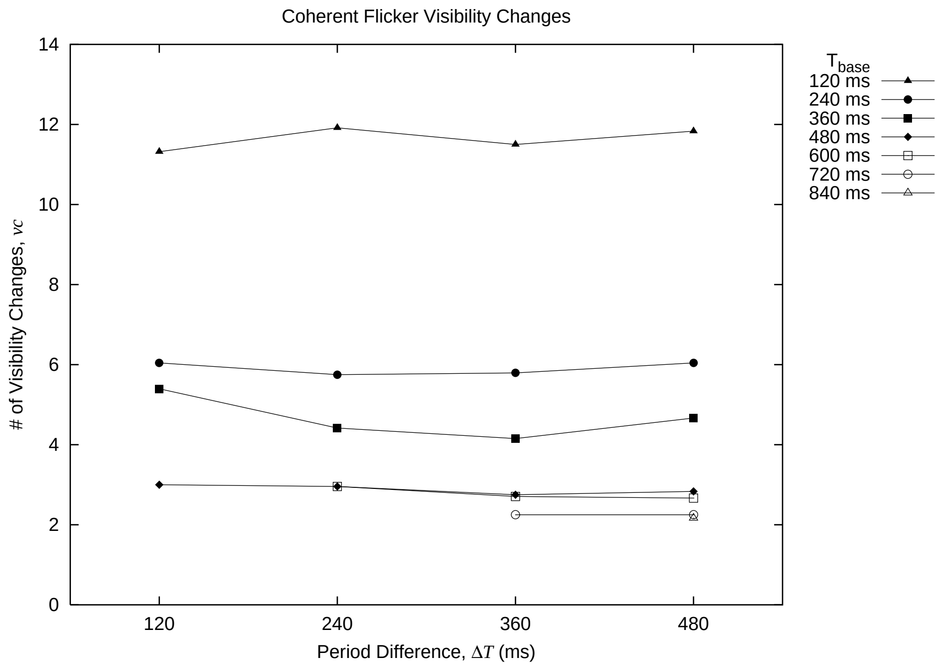


(a)

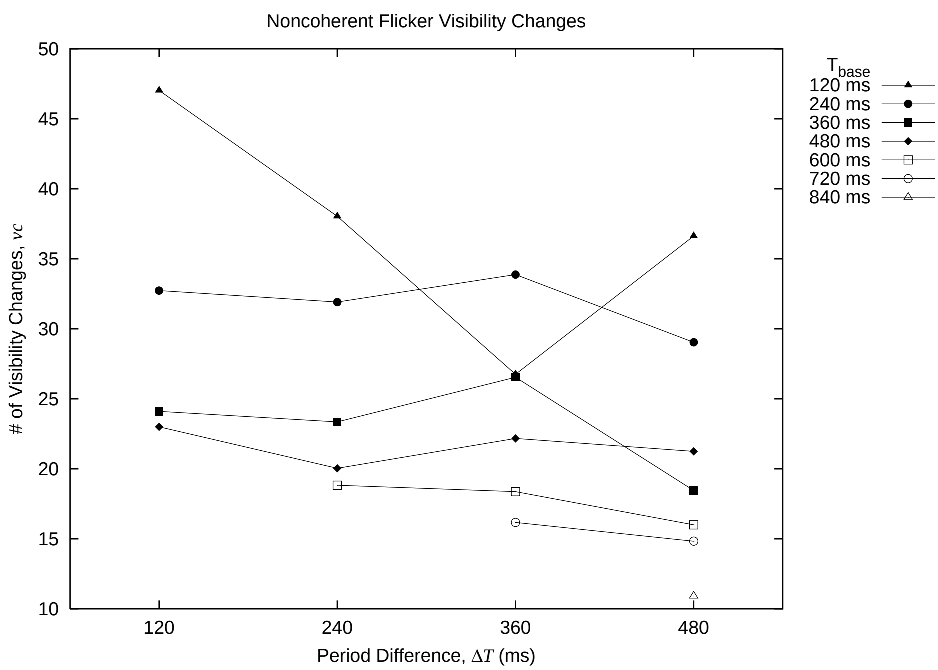


(b)

Figure 5.1: Mean error rates $\overline{e}$ are plotted versus target-background period difference ΔT for each base period T_{base}. (a) shows results from the coherent flicker sub-experiment; (b) shows results from the noncoherent flicker sub-experiment.



(a)



(b)

Figure 5.2: Mean visibility changes $\overline{vc}$ are plotted versus target-background period difference ΔT for each base period T_{base}. (a) shows results from the coherent flicker sub-experiment; (b) shows results from the noncoherent flicker sub-experiment.

Chapter 6

Weather Application

In this chapter we provide the details of a practical application in the meteorological domain using simple linear motion and flicker in a glyph-based visualization. We used a data set recorded by the Intergovernmental Panel on Climate Change over the years 1961 to 1990. The data set contained average monthly surface climate conditions, such as temperature, precipitation, cloud cover, wind speed, and pressure, measured at $\frac{1}{2}^{\circ}$ latitude and longitude increments spanning the entire world.

One of the limiting factors that determines how many sample points can be visualized using motion is processor speed. In order to achieve acceptable frame rates that give the appearance of smooth motion, the display needs to be updated at least 15 times per second. With a large data set, it may not be feasible to update the locations and visibility of all elements in that short amount of time. In our application, we visualize the Eastern portion of the United States, as far west as central Texas, which contains approximately 14,000 data points.

One of the strengths of linear motion, found through visual search experiments, is its ability to segregate elements into groups. From this we decided to map various climate conditions to linear motion in order to test its effectiveness in a practical visualization. Our visualization used *pexels* (perceptual texture elements) to represent the values at each sample point of the data set. Each pexel was in the form of a yellow square, and its position within the display was given by the latitude and longitude of the corresponding sample point. The process of mapping an attribute value to the value of a visual feature (e.g. direction of motion) is basically a binning problem. We chose to use 7 bins so we needed 7 directions of motion ($-90°$ to $90°$ in $30°$ increments). An attribute value was then mapped to a bin by comparing its value to the minimum and maximum values of that attribute. Values in the first quantile were mapped to $-90°$, in the second quantile to $-60°$, and so forth.

We first chose to map temperature to linear motion. We expected to see more or less horizontal bands of elements because temperature changes almost uniformly from North to South. Linear motion did in fact produce this phenomenon. We also mapped precipitation to linear motion. From this mapping it was easy to see the higher spatial frequency that precipitation data exhibits, especially during the month of May. We noticed the following effects of linear motion in our visualization:

- Although it was easy to group similar elements that were near each other, it was difficult to determine if spatially dispersed clusters of elements were moving in the same direction.
- Comparison between values of neighboring groups was easy. For example, it was easy to tell if the direction of one group had a greater slope, and thus a higher value. However,

it was difficult to determine the magnitude of difference between groups.

- Linear motion was able to present an overall trend to the data. For instance, it was easy to see that some months are hotter than others because the overall motion pattern of pexels was upward versus downward.

- Unfortunately, it was difficult to identify pexels with a specific direction of motion, especially if they were amongst pexels with varying directions. This is because the motion of a group of neighboring pexels can influence our perception of the direction of another group of pexels. For example, a small patch of horizontally moving pexels within a larger field of vertically moving pexels may appear to move diagonally.

Next, we tested the effects of flicker in our weather visualization. With flicker, we must be concerned with the rate at which the display is updated because the maximum frequency of flicker that can be produced is $\frac{1}{2}$ of the display update frequency. For example, if the display is updated 20 times per second (20 Hz), then the fastest produceable flicker rate is 10 Hz. In order to avoid aliasing problems (the result of trying to use a frequency greater than the maximum flicker frequency), we tied the values of flicker in our visualization to the display rate. Thus, there would never be a case when a high attribute value appeared as a lower value, the result of an aliasing problem. Given a display rate r, the 7 possible flicker rates were, $2r$, $4r$, $8r$, $16r$, $32r$, $64r$, and $128r$, with high attribute values mapped to a fast flicker rate.

One difference between our experimental flicker setup and our use of flicker in a practical visualization is the appearance of a pexel during its ‘off’ stage. In our visual search experiment, we made the pexel completely invisible. We found this to be somewhat distracting in an actual visualization because pexels seem to appear out of nowhere. To remedy this, instead of disappearing completely, we made pexels blend in with the background, but still be visible, during an 'off' stage.

In testing flicker, we first mapped temperature to flicker. The same bands of elements with similar temperatures that were seen with linear motion were also seen with flicker. See Figure 6.1 for an example of this behavior. We also mapped precipitation to flicker and found that flicker was good at grouping high spatial frequency data. We found that flicker had the following effects in our visualization:

- The boundaries between groups of pexels were easily distinguishable.
- It was possible to group spatially dispersed clusters of pexels with the same flicker frequency.
- Small clusters of outliers within a larger cluster of elements were quickly noticeable.
- Comparison of flicker rates between groups was easy, although it was difficult to determine by how much two groups differed.
- It was difficult to identify pexels with a specific attribute value. By using the display rate as a base for flicker rate, it was impossible to determine, without a full range of flicker values for comparison, why a pexel blinked at the rate it did. A slow flicker rate could be caused by either a low attribute value or a slow display rate. Displaying a legend containing the range of possible flicker rates could help alleviate this problem.

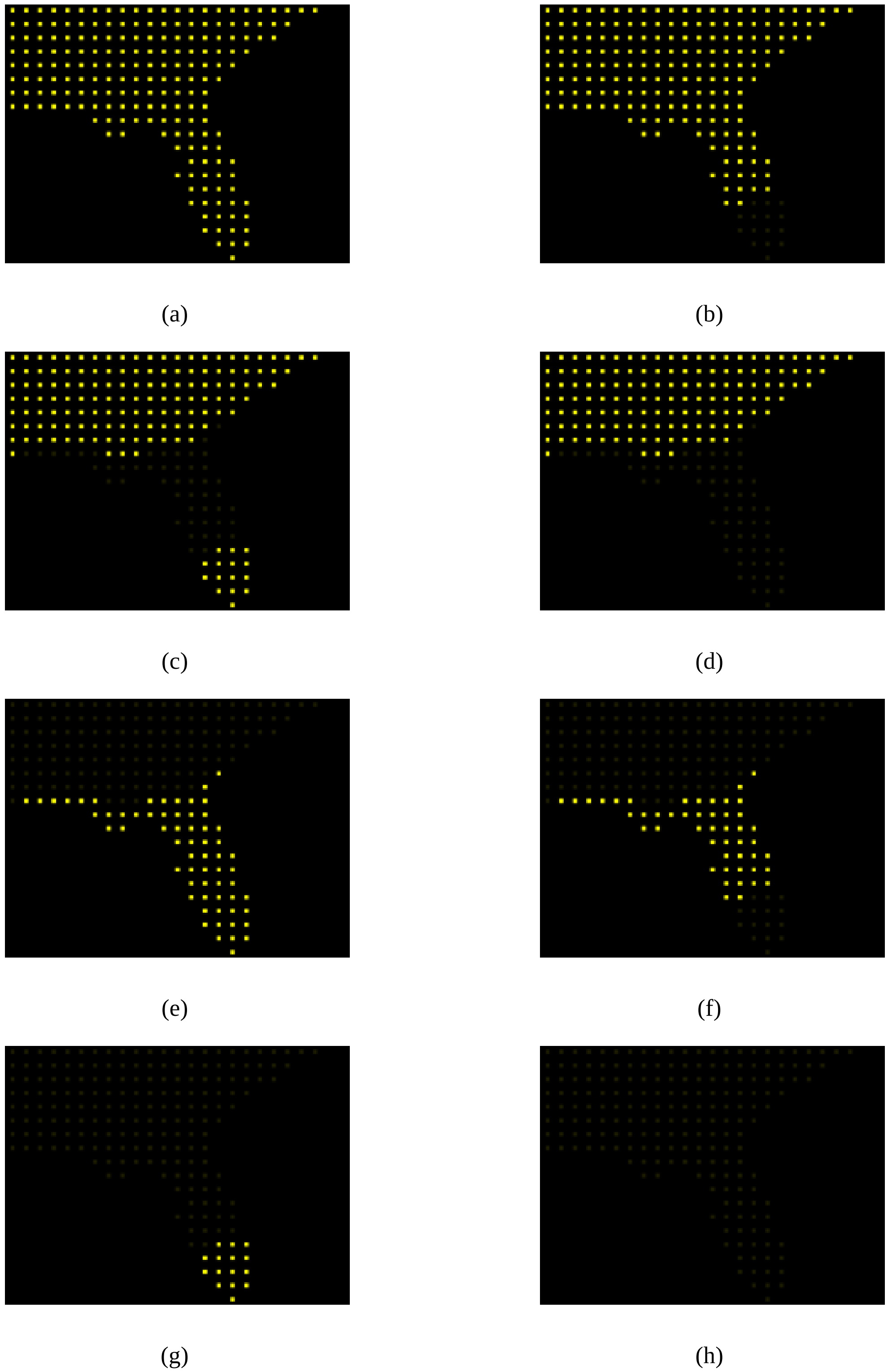


Figure 6.1: An example of a weather visualization with temperature mapped to flicker. Shown are a sequence of frames (a-h) depicting the average temperatures for the month of January in Florida and surrounding states.

Chapter 7

Conclusions and Future Work

Visualizations provide a means to analyze and explore large sets of data. Several techniques exist to present data visually, including glyph-based visualizations where each glyph encodes multiple attribute values of a single sample point. The effectiveness of a glyph's visual features such as color, form, texture, and density have been studied previously. We were interested in how simple motion of glyphs could be used in visualizations. We conducted two user studies to ascertain the properties of direction of simple linear motion and flicker relevant to visualization. We then applied the knowledge gained from the results of these studies to a visualization of weather data.

From our first experiment, we found that viewers were able to rapidly and accurately detect a target group of elements within a background when the direction of the groups differed by at least 30°, regardless of the specific direction of any one group. This suggested that when direction of motion is used as a visual feature, directions of groups with similar values should differ by at least 30°, thus giving a maximum of 12 possible direction categories.

In our second experiment, we found that viewers were able to rapidly and accurately detect a target group of elements that flickered at a rate different than the background elements only if the phases of all elements were equal. The actual difference in frequency and specific frequencies of groups were irrelevant for the rates we tested.

Through our experiments and informal analysis of our practical visualization of weather data we found that direction of motion and flicker can be used to aid the task of discriminating between groups of elements. It is easy to see where boundaries between groups are located. It is unclear whether direction of motion and flicker are well suited for the task of identifying the absolute values of flicker or direction of motion for a particular element. It does seem likely that viewers are able to compare elements to determine if one has a higher value than another, such as element *a* is blinking faster than element *b*, or the direction of element *a* is steeper than element *b*. However, further user studies are needed to confirm the conditions in a visualization under which this may be possible.

Often times a user may want to view several attributes of a multi-dimensional data set at once. Therefore, a combination of visual features is required to encode the values of attributes. Previous studies in cognitive psychology have shown the effects of conjunction searches of motion with color, shape, and stereoscopic depth. We would be interested in using these findings in a visualization setting in addition to conducting further user studies to determine how simple motion can be combined with other visual features.

Other types and properties of motion may be effective in visualizations and should be explored further. An obvious property of simple linear motion that could be used is speed of motion. Research from psychophysics and psychology suggest that the visual system is capable of detecting differences in speed. An oscillation motion may also have advantages in visualization.

Bibliography

[ACSW96] Alexander Aiken, Jolly Chen, Michael Stonebraker, and Allison Woodruff. Tioga-2: A direct manipulation database visualization environment. In *ICDE*, pages 208–217, 1996.

[BA02] E. Bullitt and S. Aylward. Fast, high-quality, volume rendering of vascular anatomy via segmentation. In *IEEE-TMI*, 2002.

[BP01] Paul Barford and David Plonka. Characteristics of network traffic flow anomalies. In *Proceedings of the First ACM SIGCOMM Workshop on Internet Measurement Workshop*, pages 69–73. ACM Press, 2001.

[Bra98] M. J. Bravo. A global process in motion segregation. *Vision Research*, 38:853–864, 1998.

[Bro65] John Lott Brown. *Vision and Visual Perception*, chapter 6, pages 251–320. John Wiley & Sons, Inc., 1965.

[BS87] K. Ball and R. Sekuler. Direction-specific improvement in motion discrimination. *Vision Research*, 27:953–965, 1987.

[BWC01a] L. Bartram, C. Ware, and T. Calvert. Filtering and integrating visual information with motion. In *Proceedings on Information Visualization*, pages 66–79, 2001.

[BWC01b] L. Bartram, C. Ware, and T. Calvert. Moving icons: detection and distraction. In *Proceedings of Interact*, pages 157–166, 2001.

[CAL+97] Isabel F. Cruz, M. Averbuch, Wendy T. Lucas, Melissa Radzyminski, and Kirby Zhang. Delaunay: a database visualization system. In *Proceedings of the 1997 ACM SIGMOD international conference on Management of data*, pages 510–513. ACM Press, 1997.

[Che73] Herman Chernoff. The use of faces to represent points in k-dimensional space graphically. *Journal of the American Statistical Association*, 68(342), 1973.

[CHY99] N.D. Cook, T. Hayashi, and N. Yoshida. Visualizing the atomic nucleus. *Computer Graphics and Applications*, 19:54–60, 1999.

[DBO88] Bart De Bruyn and Guy A. Orban. Human velocity and direction discrimination measured with random dot patterns. *Vision Research*, 28:1323–1335, 1988.

[DD92] P. Driver, J. McLeod and Z. Dienes. Motion coherence and conjunction search: Implications for guided search theory. *Perception & Psychophysics*, 51:79–85, 1992.

[DH02] Brent M. Dennis and Christopher G. Healey. Assisted navigation for large information spaces. In *Proceedings of the conference on Visualization '02*, pages 419–426. IEEE Computer Society, 2002.

[GLI98] Georges Grinstein, Sharon Laskowski, and Alfred Inselberg. Key problems and thorny issues in multidimensional visualization. In *Proceedings of the conference on Visualization '98*, pages 505–506. IEEE Computer Society Press, 1998.

[Gra65] Clarence. H. Graham. *Vision and Visual Perception*, chapter 2. John Wiley & Sons, Inc., 1965.

[HE96] Christopher G. Healey and James T. Enns. A perceptual colour segmentation algorithm. Technical Report TR-96-09, Department of Computer Science, University of British Columbia, 1996.

[HE98] Christopher G. Healey and James T. Enns. Building perceptual textures to visualize multidimensional datasets. In David Ebert, Hans Hagen, and Holly Rushmeier, editors, *IEEE Visualization '98*, pages 111–118, 1998.

[HE99] Christopher G. Healey and James T. Enns. Large datasets at a glance: Combining textures and colors in scientific visualization. *IEEE Transactions on Visualization and Computer Graphics*, 5(2):145–167, 1999.

[Hea96] Christopher G. Healey. Choosing effective colours for data visualization. In *Proceedings Visualization '96*, pages 263–270, San Francisco, California, 1996.

[HSAE99] Christopher G. Healey, Robert St. Amant, and Mahmoud Elhaddad. ViA: A perceptual visualization assistant. In *28th Workshop on Advanced Imagery Pattern Recognition (AIPR-99)*, pages 1–11, Washington, DC, 1999.

[IFG+98] Victoria Interrante, James Ferwerda, Rich Gossweiler, Christopher G. Healey, and Penny Rheingans. Applications of visual perception in computer graphics. In *SIGGRAPH 98 Course 32*, Orlando, Florida, 1998.

[JS01] R. Jesse and T. Strothotte. Motion enhanced visualization in support of information fusion. In *Proceedings of International Conference on Imaging Science, Systems, and Technology*, pages 492–497. CSREA Press, 2001.

[Ker90] G. G. Kerlick. Moving iconic objects in scientific visualization. In *Proceedings Visualization '90*, pages 124–130. IEEE, 1990.

[KFL91] S. Kochhar, M. Friedell, and M. LaPolla. Cooperative, computer-aided design of scientific visualizations. In *Proceedings of the conference on Visualization '91*, pages 306–313, San Diego, CA, 1991. IEEE Computer Society Press.

[KK95] Daniel A. Keim and Hans-Peter Kriegel. Possibilities and limits in visualizing large amounts of multidimensional data. pages 127–141, 1995.

[Koc94] S. Kochhar. Ccad: A paradigm for human-computer cooperation in design. *Computer Graphics and Applications*, 14:54–65, 1994.

[MDB87] Bruce H. McCormick, Thomas A. Defanti, and M. D. Brown. Visualization in scientific computing. *Computer Graphics*, 21:1–14, 1987.

[MDC88] P. McLeod, J. Driver, and J. Crisp. Visual search for a conjunction of movement and form is parallel. *Nature*, 332:154–155, 1988.

[Mil] George A. Miller. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *The Psychological Review*, 63:81–97.

[MLGQ99] Nestor Matthews, Zili Liu, Bard J. Geesaman, and Ning Qian. Perceptual learning on orientation and direction discrimination. *Vision Research*, 39:3692–3701, 1999.

[Nak85] K. Nakayama. Biological image motion processing: A review. *Vision Research*, 25:625–660, 1985.

[Not93] Hans-Christoph Nothdurft. The role of features in preattentive vision: comparison of orientation, motion and color cues. *Vision Research*, 33:1937–1958, 1993.

[NS86] K. Nakayama and G. H. Silverman. Serial and parallel processing of visual feature conjunctions. *Nature*, 320:264–265, 1986.

[RDF94] P. Robertson and L. De Ferrari. *Systematic Approaches to Visualization: Is a Reference Model Needed?* Academic Press, 1994.

[Spe99] William M. Spears. An overview of multidimensional visualization techniques. In Trevor D. Collins, editor, *Evolutionary Computation Visualization*, pages 104–105, Orlando, Florida, USA, 13 1999.

[TG80] A. Treisman and G. & Gelade. A feature integration theory of attention. *Cognitive Psychology*, 12:97–136, 1980.

[Tre82] A. Treisman. Perceptual grouping and attention in visual search for features and for objects. *Journal of Experimental Psychology: Human Perception and Performance*, 8:194–214, 1982.

[Tre99] L. Treinish. Task-specific visualization design. *IEEE Computer Graphics and Applications*, 19:72–77, 1999.

[Tuf83] Edward R. Tufte. *The Visual Display of Quantitative Information*. Graphics Press, 1983.

[TYDV04] Tatsuto Takeuchi, Kazuhiko Yokosawa, and Karen K. De Valois. Texture segregation by motion under low luminance levels. *Vision Research*, 44:157–166, 2004.

[Wri95] W. Wright. Research report: information animation applications in the capital markets. In *Proceedings on Information Visualization*, pages 19–25. IEEE, 1995.