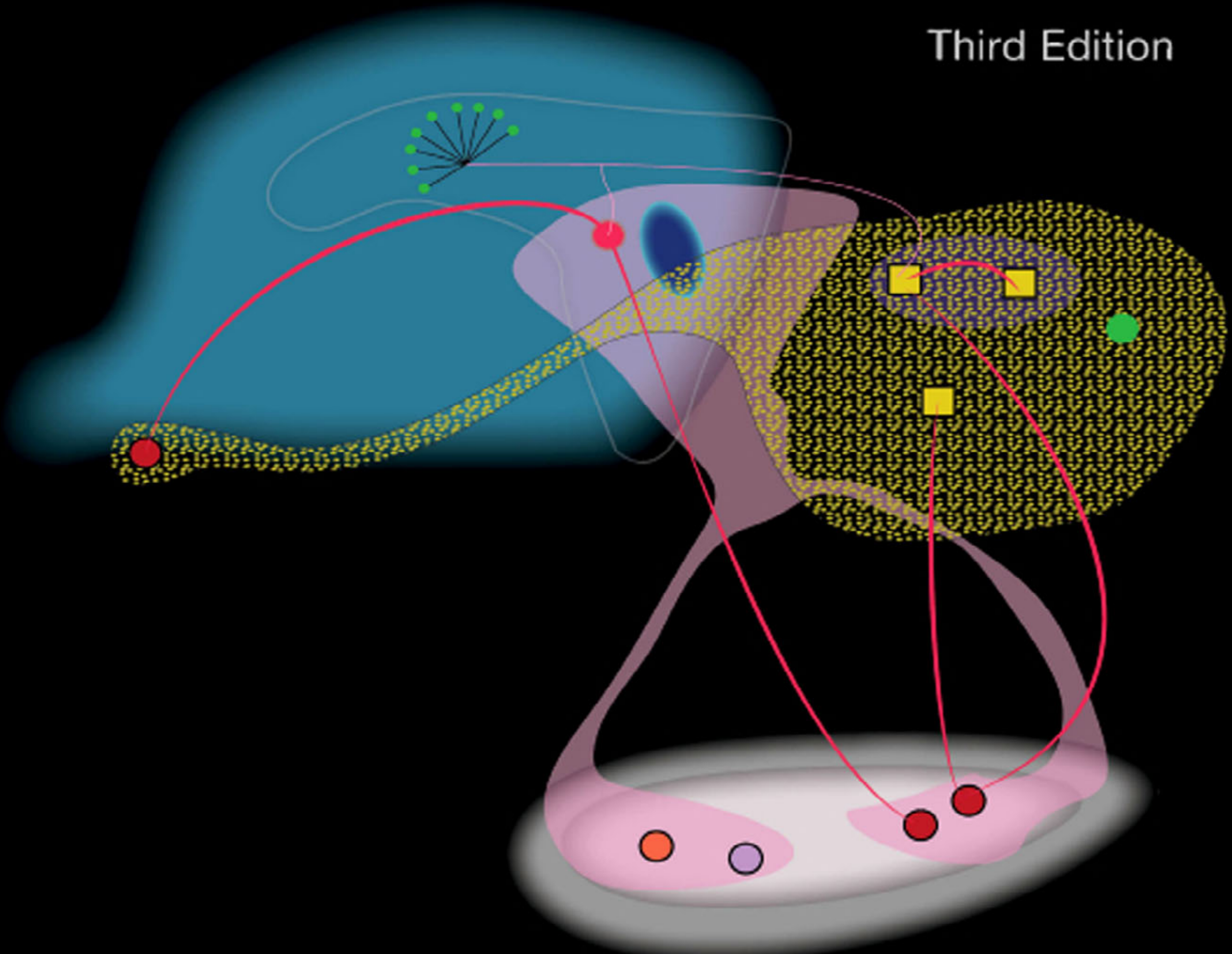
Information Visualization

PERCEPTION FOR DESIGN

Third Edition



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Colin Ware

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Third Edition

Colin Ware

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Contents

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Preface

There are two major changes in this latest edition of *Information Visualization: Perception for Design*. The first is intended to make the design implications of research in perception clearer. To this end, 168 explicit guidelines for the design of visualizations have been added to the text in highlighted boxes. These guidelines should be taken as suggestions to support design decisions, not as hard and fast rules. Designing visualizations is a complex task, and it is not possible with a succinct guideline to set out all the circumstances under which a particular rule may apply. Graphic designers must take into account interactions between small symbols and large areas of color and texture as well as shading effects, shape effects, the grouping of symbols, and so on. Different tasks may dictate changes in what should be highlighted and what should be deemphasized. Often a designer must use an existing color scheme or symbol set, and this also constrains the design problem. Because of this complexity, it is important to understand the theory behind a guideline before it is applied; understanding the mechanisms of perception and the processes of visual thinking can make it clear when and how that guideline should be applied and when it does not apply.

The second major change is an increased emphasis on the process of visual thinking. The book now more fully incorporates the modern view that perception is an active process in which every part of the visual system is retuned several times a second to meet the needs of the current visual task. The greatest change is a radical reworking of the final chapter, which now sets out the key components of the architecture of the visual brain and follows this with a description of ten visual thinking algorithms. These describe how people think using common visualization tools and techniques. They are intended to help a designer take a visualization design problem and create a novel and well-designed visual thinking tool.

In addition to these major changes, the book has been revised and updated throughout to take recent research into account. Hundreds of new references have been added, and most of the figures have been redrawn to take advantage of full-color printing.

Now let me tell you how this book came about. In 1973, after I had completed my master's degree in the psychology of vision, I was frustrated with the overly focused academic way of studying perception. Inspired by the legacy of freedom that seemed to be in the air in the late 1960s and early 1970s, I decided to become an artist and explore perception in a very different way. But after three years with only very small success, I returned, chastened, to the academic fold, though with a broader outlook, a great respect for artists, and a growing interest in the relationship between the way we present information and the way we see. After obtaining a doctorate in the psychology of perception at the University of Toronto, I still did not know what to do next. I moved into computer science, via the University of Waterloo and another degree, and have been working on data visualization, in one way or another, ever since. In a way, this book is a direct result of my ongoing attempt to reconcile the scientific study of perception with the need to convey meaningful information. It is about art in the sense that "form should follow function," and it is about science because the science of perception can tell us what kinds of patterns are most readily perceived.

Why should we be interested in visualization? Because the human visual system is a pattern seeker of enormous power and subtlety. The eye and the visual cortex of the brain form a massively parallel processor that provides the highest bandwidth channel into human cognitive centers. At higher levels of processing, perception and cognition are closely interrelated, which is the reason why the words "understanding" and "seeing" are synonymous. However, the visual system has its own rules. We can easily see patterns presented in certain ways, but if they are presented in other ways they become invisible. Thus, for example, the word *goggle*, shown in the accompanying figure, is much more visible in the version shown at the bottom than in the one at the top. This is despite the fact that identical parts of the letters are visible in each case and in the lower figure there is more irrelevant "noise" than in the upper figure. The rule that applies here, apparently, is that when the missing pieces are interpreted as foreground objects then continuity between the background letter fragments is easier to infer. The more general point is that when data is presented in certain ways the patterns can be readily perceived. If we can understand how perception works, our knowledge can be translated into guidelines for displaying information. Following perception-based rules, we can present our data in such a way that the important and informative patterns stand out. If we disobey these rules, our data will be incomprehensible or misleading.

This is a book about what the science of perception can tell us about visualization. There is a gold mine of information about how we see to be found in more than a century of work by vision researchers. The purpose of this book is to extract from that large body of research literature those design principles that apply to displaying information effectively.

Visualization can be approached in many ways. It can be studied in the art-school tradition of graphic design. It can be studied within computer graphics as an area concerned with the algorithms needed to display data. It can be studied as part of semiotics, the constructivist approach to symbol systems. These are valid approaches, but a scientific approach based on perception uniquely promises design rules that transcend the vagaries of design fashion, being based on the relatively stable structure of the human visual system.

The study of perception by psychologists and neuroscientists has advanced enormously over the past three decades, and it is possible to say a great deal about how we see that is relevant to data visualization. Unfortunately, much of this information is stored in highly specialized journals and usually couched in language that is accessible only to the research scientist. The research literature concerning human perception is voluminous. Several hundred new papers are published every month, and a surprising number of them have some application in information display. This information can be extremely useful in helping us design better displays, both by avoiding mistakes and by coming up with original solutions. *Information Visualization: Perception for Design* is intended to make this science and its applications available to the nonspecialist. It should be of interest to anyone concerned with displaying data effectively. It is designed with a number of audiences in mind: multimedia designers specializing in visualization, researchers in both industry and academia, and anyone who has a deep interest in effective information display. The book presents extensive technical information about various visual acuities, thresholds, and other basic properties of human vision. It also contains, where possible, specific guidelines and recommendations.

The book is organized according to bottom-up perceptual principles. The first chapter provides a general conceptual framework and discusses the theoretical context for a vision-science-based approach. The next four chapters discuss what can be considered to be the low-level perceptual elements of vision, color, texture, motion, and elements of form. These primitives of vision tell us about the design of attention-grabbing features and the best ways of coding data so that one object will be distinct from another. The later chapters move on to discussing what it takes to perceive patterns in data: first two-dimensional pattern perception, and later three-dimensional space perception. Visualization design, data space navigation, interaction techniques, and visual problem solving are all discussed.

Here is a road map to the book: In general, the pattern for each chapter is first to describe some aspect of human vision and then to apply this information to some problem in visualization. The first chapters provide a foundation of knowledge on which the later chapters are built. Nevertheless, it is perfectly reasonable to randomly access the book to learn about specific topics. When it is needed, missing background information can be obtained by consulting the index.

Chapter 1: Foundation for a Science of Data Visualization A conceptual framework for visualization design is based on human perception. The nature of claims about sensory representations is articulated, with special attention paid to the work of perception theorist J.J. Gibson. This analysis is used to define the differences between a design-based approach and an approach based on the science of perception. A classification of abstract data classes is provided as the basis for mapping data to visual representations.

Chapter 2: The Environment, Optics, Resolution, and the Display This chapter deals with the basic inputs to perception. It begins with the physics of light and the way light interacts with objects in the environment. Central concepts include the structure of light as it arrives at a viewpoint and the information carried by that light array about surfaces and objects available for interaction. This chapter goes on to discuss the basics of visual optics and issues such as how much detail we can resolve. Human acuity measurements are described and applied to display design.

The applications discussed include design of 3D environments, how many pixels are needed for visual display systems and how fast they should be updated, requirements for virtual-reality display systems, how much detail can be displayed using graphics and text, and detection of faint targets.

Chapter 3: Lightness, Brightness, Contrast, and Constancy The visual system does not measure the amount of light in the environment; instead, it measures *changes* in light and color. How the brain uses this information to discover properties of the surfaces of objects in the environment is presented. This is related to issues in data coding and setting up display systems.

The applications discussed include integrating the display into a viewing environment, minimal conditions under which targets will be detected, methods for creating grayscales to code data, and errors that occur because of contrast effects.

Chapter 4: Color This chapter introduces the science of color vision, starting with receptors and trichromacy theory. Color measurement systems and color standards are presented. The standard equations for the CIE standard and the *CIEluv* uniform color space are given. Opponent process theory is introduced and related to the way data should be displayed using luminance and chrominance.

The applications discussed include color measurement and specification, color selection interfaces, color coding, pseudocolor sequences for mapping, color reproduction, and color for multidimensional discrete data.

Chapter 5: Visual Salience and Finding Information A "searchlight" model of visual attention is introduced to describe the way eye movements are used to sweep for information. The bulk of the chapter is taken up with a description of the massively parallel processes whereby the visual image is broken into elements of color, form, and motion. Preattentive processing theory is applied to critical issues of making one data object distinct from another. Methods for coding data so it can be perceptually integrated or separated are discussed.

The applications discussed include display for rapid comprehension, information coding, the use of texture for data coding, the design of symbology, and multidimensional discrete data display.

Chapter 6: Static and Moving Patterns This chapter looks at the process whereby the brain segments the world into regions and finds links, structure, and prototypical objects. These are converted into a set of design guidelines for information display.

The applications discussed include display of data so that patterns can be perceived, information layout, node–link diagrams, and layered displays.

Chapter 7: Visual Objects and Data Objects Both image-based and 3D-structure-based theories of object perception are reviewed. The concept of the object display is introduced as a method for using visual objects to organize information.

The applications discussed include presenting image data, using 3D structures to organize information, and the object display.

Chapter 8: Space Perception and the Display of Data in Space Increasingly, information display is being done in 3D virtual spaces as opposed to the 2D screen-based layouts.

The different kinds of spatial cues and the ways we perceive them are introduced. The latter half of the chapter is taken up with a set of seven spatial tasks and the perceptual issues associated with each.

The applications discussed include 3D information displays, stereo displays, the choice of 2D versus 3D visualization, 3D graph viewing, and virtual environments.

Chapter 9: Images, Words, and Gestures Visual information and verbal information are processed in different ways and by different parts of the brain. Each has its own strengths, and often both should be combined in a presentation. This chapter addresses when visual and verbal presentation should be used and how the two kinds of information should be linked.

The applications discussed include integrating images and words, visual programming languages, and effective diagrams.

Chapter 10: Interacting with Visualizations Major interaction cycles are defined. Within this framework, low-level data manipulation, dynamic control over data views, and navigation through data spaces are discussed in turn.

The applications discussed include interacting with data, selection, scrolling, zooming interfaces, and navigation.

Chapter 11: Visual Thinking Processes This chapter begins by outlining the cognitive system involved in thinking with visualizations. The second half of the chapter provides ten common visual thinking algorithms that are widely applicable in interactive visualization. These are processes that occur partly in a computer, partly in the visual brain of the user. The output of the computer is a series of visual images that are processed through the visual system of the user. The output of the user is a set of epistemic actions, such as clicking on an object or moving a slider, which result in the visualization being modified in some way by the computer.

The applications discussed include problem solving with visualization, design of interactive systems, and creativity.

These are exciting times for visualization design. The computer technology used to produce visualizations has reached a stage at which sophisticated interactive 3D views of data can be produced on laptop and tablet computers. The trend toward more and more visual information is accelerating, and there is an explosion of new visualization techniques being invented to help us cope with our need to analyze huge and complex bodies of information. This creative phase will not last for long. With the dawn of a new technology, there is often only a short burst of creative design before the forces of standardization make what is new into what is conventional. Undoubtedly, many of the visualization techniques that are now emerging will become routine tools in the near future. Even badly designed things can become industry standards. Designing for perception can help us avoid such mistakes. If we can harness the knowledge that has accumulated regarding how perception works, we can make visualizations become more transparent windows into the world of information.

I wish to thank the many people who have helped me with this book. The people who most influenced the way I think about perception and visualization are Donald Mitchell, John Kennedy, and William Cowan. I have gained enormously by working with Larry Mayer in developing new tools to map the oceans, as well as with colleagues Kelly Booth, Dave Wells, Tim Dudely, Scott Mackenzie, and Eric Neufeld. It has been my good fortune to work with many talented graduate students and research assistants on visualization-related projects: Daniel Jessome, Richard Guitard, Timothy Lethbridge, Sean Riley, Serge Limoges, David Fowler, Stephen Osborne, Dale Chapman, Pat Cavanaugh, Ravin Balakrishnan, Mark Paton, Monica Sardesai, Cyril Gobrecht, Justine Hickey, Yanchao Li, Kathy Lowther, Li Wang, Greg Parker, Daniel Fleet, Jun Yang, Graham Sweet, Roland Arsenault, Natalie Webber, Poorang Irani, Jordan Lutes, Irina Padioukova, Glenn Franck, Lyn Bartram, Matthew Plumlee, Pete Mitchell, and Dan Pineo. Many of the ideas presented here have been refined through their efforts.

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Figure P.1 The word *goggle* is easier to read when the overlapping bars are visible. (*Redrawn from Nakayama, Shimono, and Silverman (1989)*).

About the Author

Colin Ware takes the "visual" in visualization very seriously. He has advanced degrees in both computer science (MMath, Waterloo) and the psychology of perception (Ph.D., Toronto). He has published over 150 articles in scientific and technical journals and at leading conferences, many of which relate to the use of color, texture, motion, and 3D in information visualization. In addition to his research, Professor Ware also builds useful visualization software systems. He has been involved in developing 3D interactive visualization systems for ocean mapping for over 20 years and directed the early development of the NestedVision3D system for visualizing very large networks of information. Both of these projects led to commercial spin-offs. Current projects involve tracking whales and visualizing ocean currents. He is Director of the Data Visualization Research Lab in the Center for Coastal and Ocean Mapping at the University of New Hampshire.

CHAPTER ONE

Foundations for an Applied Science of Data Visualization

In his book *The End of Science*, science writer John Horgan (1997) argued that science is finished except for the mopping up of details. He made a good case where physics is concerned. In that discipline, the remaining deep problems may involve generating so much energy as to require the harnessing of entire stars. Similarly, biology has its foundations in DNA and genetics and is now faced with the infinite but often tedious complexity of mapping genes into proteins through intricate pathways. What Horgan failed to recognize is that cognitive science has fundamental problems that are still to be solved. In particular, the mechanisms of the construction and storage of knowledge remain open questions. He implicitly adopted the physics-centric view of science, which holds that physics is the queen of sciences and in descending order come chemistry, then biology, with psychology barely acknowledged as a science at all. In this pantheon, sociology is regarded as somewhere on a par with astrology. This attitude is shortsighted. Chemistry builds on physics, enabling our understanding of materials; biology builds on chemistry, enabling us to understand the much greater complexity of living organisms; and psychology builds on neurophysiology, enabling us to understand the processes of cognition. At each level is a separate discipline greater in complexity and level of difficulty than those beneath. It is difficult to conceive of a value scale for which the mechanisms of thought are not of fundamentally greater interest and importance than the interaction of subatomic particles. Those who dismiss psychology as a pseudo-science have not been paying attention. Over the past few decades, enormous strides have been made in identifying the brain structures and cognitive mechanisms that have enabled humans to create the huge body of knowledge that now exists. But we need to go one step further and recognize that a person

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working with the aid of thinking tools is much more cognitively powerful than that person alone with his or her thoughts. This has been true for a long time. Artifacts such as paper and pens, as well as techniques such as writing and drawing, have been cognitive tools for centuries.

As Hutchins (1995) so effectively pointed out, thinking is not something that goes on entirely, or even mostly, inside people's heads. Little intellectual work is accomplished with our eyes and ears closed. Most cognition is done as a kind of interaction with cognitive tools, pencils and paper, calculators, and, increasingly, computer-based intellectual supports and information systems. Neither is cognition mostly accomplished alone with a computer. It occurs as a process in systems containing many people and many cognitive tools. Since the beginning of science, diagrams, mathematical notations, and writing have been essential tools of the scientist. Now we have powerful interactive analytic tools, such as MATLAB, Maple, Mathematica, and S-PLUS, together with databases. The entire fields of genomics and proteomics are built on computer storage and analytic tools. The social apparatus of the school system, the university, the academic journal, and the conference are obviously designed to support cognitive activity.

Cognition in engineering, banking, business, and the arts is similarly carried out through distributed cognitive systems. In each case, "thinking" occurs through interaction between individuals, using cognitive tools and operating within social networks. Hence, cognitive systems theory is a much broader discipline than psychology. This is emerging as the most interesting, difficult, and complex, yet fundamentally the most important, of sciences.

Visualizations are an increasingly important part of cognitive systems. Visual displays provide the highest bandwidth channel from the computer to the human. Indeed, we acquire more information through vision than through all of the other senses combined. The 20 billion or so neurons of the brain devoted to analyzing visual information provide a pattern-finding mechanism that is a fundamental component in much of our cognitive activity. Improving cognitive systems often means optimizing the search for data and making it easier to see important patterns. An individual working with a computer-based visual thinking tool is a cognitive system where the critical components are, on one side, the human visual system, a flexible pattern finder coupled with an adaptive decision-making mechanism, and, on the other side, the computational power and vast information resources of a computer coupled to the World Wide Web. Interactive visualization is the interface between the two sides. Improving this interface can substantially improve the performance of the entire system.

Until recently, the term *visualization* meant constructing a visual image in the mind (Little et al., 1972). It has now come to mean something more like a graphical representation of data or concepts. Thus, from being an internal construct of the mind, a visualization has become an external artifact supporting decision making. The way visualizations can function as cognitive tools is the subject of this book.

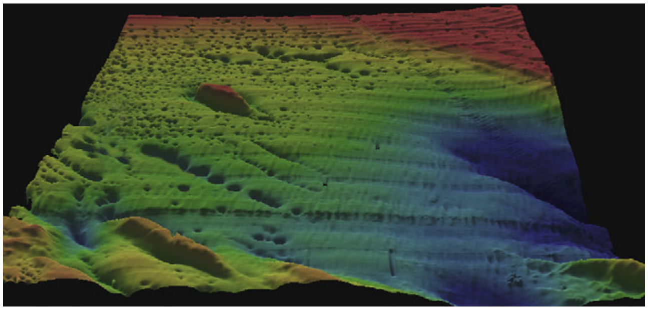

Figure 1.1 Passamoquoddy Bay visualization. (*Data courtesy of the Canadian Hydrographic Service*.)

One of the greatest benefits of data visualization is the sheer quantity of information that can be rapidly interpreted if it is presented well. Figure 1.1 shows a visualization derived from a multibeam echo sounder scanning part of Passamoquoddy Bay, between Maine in the United States, and New Brunswick in Canada, where the tides are the highest in the world. Approximately one million measurements were made. Traditionally, this kind of data is presented in the form of a nautical chart with contours and spot soundings; however, when the data is converted to a height field and displayed using standard computer graphics techniques, many things become visible that were previously invisible on the chart. A pattern of features called *pockmarks* can immediately be seen, and it is easy to see how they form lines. Also visible are various problems with the data. The linear ripples (not aligned with the pockmarks) are errors in the data because the roll of the ship that took the measurements was not properly taken into account.

The Passamoquoddy Bay image highlights a number of the advantages of visualization:

- Visualization provides an ability to comprehend huge amounts of data. The important information from more than a million measurements is immediately available.
- Visualization allows the perception of emergent properties that were not anticipated. In this visualization, the fact that the pockmarks appear in lines is immediately evident. The perception of a pattern can often be the basis of a new insight. In this case, the pockmarks align with the direction of geological faults, suggesting a cause. They may be due to the release of gas.
- Visualization often enables problems with the data to become immediately apparent. A visualization commonly reveals things not only about the data itself but also about the way it is collected. With an appropriate visualization, errors and artifacts in the data often jump out at you. For this reason, visualizations can be invaluable in quality control.

- Visualization facilitates understanding of both large-scale and small-scale features of the data. It can be especially valuable in allowing the perception of patterns linking local features.
- Visualization facilitates hypothesis formation. For example, the visualization in Figure 1.1 led to questions about the how the pockmarks might have formed and motivated a research paper concerning the geological significance of the features (Gray et al., 1997).

Visualization Stages

The process of data visualization includes four basic stages, combined in a number of feedback loops. These are illustrated in Figure 1.2. The four stages consist of:

- The collection and storage of data.
- A preprocessing stage designed to transform the data into something that is easier to manipulate. Usually there is some form of data reduction to reveal selected aspects. Data exploration is the process of changing the subset that is currently being viewed.
- Mapping from the selected data to a visual representation, which is accomplished through computer algorithms that produce an image on the screen. User input can transform the mappings, highlight subsets, or transform the view. Generally this is done on the user's own computer.
- The human perceptual and cognitive system (the perceiver).

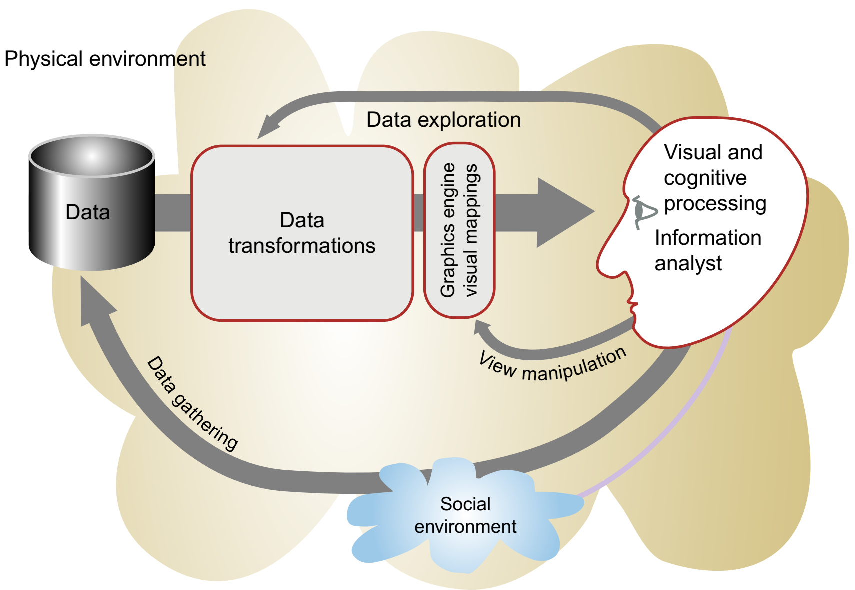

Figure 1.2 The visualization process.

The longest feedback loop involves gathering data. A data seeker, such as a scientist or a stock-market analyst, may choose to gather more data to follow up on an interesting lead. Another loop controls the computational preprocessing that takes place prior to visualization. The analyst may feel that if the data is subjected to a certain transformation prior to visualization, it can be persuaded to give up its meaning. Sometimes the process is a search through a very large volume of data to find an important nugget. Finally, the visualization process itself may be highly interactive; for example, in three-dimensional (3D) data visualization, the scientist may "fly" to a different vantage point to better understand the emerging structures. Alternatively, a computer mouse may be used interactively to select the parameter ranges that are most interesting.

Both the physical environment and the social environment are involved in the data-gathering loop. The physical environment is a source of data, while the social environment determines in subtle and complex ways what is collected and how it is interpreted. In this book, the emphasis is on data, perception, and the various tasks to which visualization may be applied. In general, algorithms are discussed only insofar as they are related to perception. The computer is treated, with some reservations, as a universal tool for producing interactive graphics. This means that once we figure out the best way to visualize data for a particular task, we assume that we can construct algorithms to create the appropriate images.

The critical question is how best to transform the data into something that people can understand for optimal decision making. Before plunging into a detailed analysis of human perception and how it applies in practice, however, we must establish the conceptual basis for the endeavor. The purpose of this discussion is to stake out a theoretical framework wherein claims about visualizations being "visually efficient" or "natural" can be pinned down in the form of testable predictions.

Experimental Semiotics Based on Perception

This book is about the applied science of visualization. It is based on the idea that the value of a good visualization is that it lets us see patterns in data and therefore the science of pattern perception can provide a basis for design decisions, but the claim that visualization can be based on science may be disputed. Let's look at the alternative view. Some scholars argue that visualization is best understood as a kind of learned language and not as a science at all. In essence, their argument is the following. Visualization is about diagrams and how they can convey meaning. Diagrams are made up of symbols, and symbols are based on social interaction. The meaning of a symbol is normally understood to be created by convention, which is established in the course of person-to-person communication. Diagrams are arbitrary and are effective in much the same way as the written words on this page are effective—we must learn the conventions of the language, and the better we learn them the clearer that language will be. Thus, one diagram may ultimately be as good as another; it is just a matter of learning the code, and the laws of perception are largely irrelevant.

This view has strong philosophical proponents from the classical field of semiotics. Although it is not the position adopted here, the debate can help us define where vision research can assist us in designing better visualizations and where we would be wise to consult a graphic designer trained in an art college.

Semiotics of Graphics

The study of symbols and how they convey meaning is called *semiotics*. This discipline was originated in the United States by C. S. Peirce and later developed in Europe by the French philosopher and linguist Ferdinand de Saussure (1959). Semiotics has been dominated mostly by philosophers and by those who construct arguments based on example rather than on formal experiment. In his great masterwork, *Semiology of Graphics*, Jacques Bertin (1983) attempted to classify all graphic marks in terms of how they could express data. For the most part, this work is based on his own judgment, although it is a highly trained and sensitive judgment. There are few references to theories of perception or scientific studies.

It is often claimed that visual languages are easy to learn and use, but what do we mean by the term *visual language*? Clearly not the writing on this page. Reading and writing take years of education to master, and it can take almost as long to master some diagrams. Figure 1.3 shows three examples of languages that have some claim to being visual. The first example of visual language is based on a cave painting. We can readily interpret human figures and infer that the people are using bows and arrows to hunt deer. The second example is a schematic diagram showing the interaction between a person and a computer in a virtual environment system; the brain in the diagram is a simplified picture, but it is a part of the anatomy that few have directly perceived. The arrows show data flows and are arbitrary conventions, as are the printed words.

The third example is the expression of a mathematical equation that is utterly obscure to all but the initiated. These examples clearly show that some visual languages are easier to "read" than others. But why? Perhaps it is simply that we have more experience with the kind of pictorial image shown in the cave painting and less with the

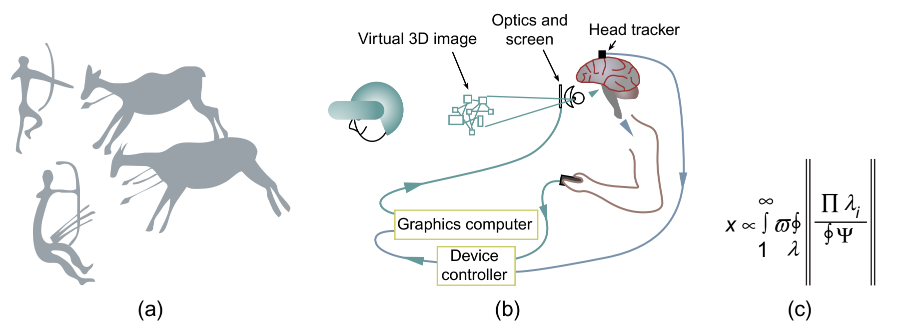

Figure 1.3 Three graphics. Each could be said to be a visualization.

mathematical notation. Perhaps the concepts expressed in the cave painting are more familiar than those in the equation.

The most profound threat to the idea that there can be a scientific basis for visualization design originates with Saussure. He defined a principle of arbitrariness as applying to the relationship between the symbol and the thing that is signified. Saussure was also a founding member of a group of structuralist philosophers and anthropologists who, although they disagreed on many fundamental issues, were unified in their general insistence that truth is relative to its social context. Meaning in one culture may be nonsense in another. A trash can as a visual symbol for deletion is meaningful only to those who know how trash cans are used. Thinkers such as Levi-Strauss, Barthes, and Lacan have condemned the cultural imperialism and intellectual arrogance implicit in applying our intellects to characterizing other cultures as "primitive." As a result, they have developed the theory that all meaning is relative to the culture. Indeed, meaning is created by society. They claim that we can interpret another culture only in the context of our own culture and using the tools of our own language. Languages are conventional means of communication in which the meanings of symbols are established through custom. Their point is that no one representation is "better" than another. All representations have value. All are meaningful to those who understand them and agree to their meanings. Because it seems entirely reasonable to consider visualizations as communications, their arguments strike at the root of the idea that there can be an applied science of visualization with the goal of establishing specific guidelines for better representations. We reject this view and instead argue that it is possible to have a new semiotics based not on philosophical claims for symbols being arbitrary, but instead on scientific evidence.

Are Pictures Arbitrary?

The question of whether pictures and diagrams are purely conventional or are perceptual symbols with special properties has been the subject of considerable scientific investigation. A good place to begin reviewing the evidence is the perception of pictures. There has been a debate over the past century between those who claim that pictures are every bit as arbitrary as words and those who believe that there may be a measure of similarity between pictures and the things that they represent. This debate is crucial to the theory presented here; if even "realistic" pictures do not embody a sensory language, it will be impossible to make claims that certain diagrams and other visualizations are better designed perceptually.

The nominalist philosopher, Nelson Goodman (1968), has delivered some of the more forceful attacks on the notion of similarity in pictures:

> *Realistic representation, in brief, depends not upon imitation or illusion or information but upon inculcation. Almost any picture may represent almost anything; that is, given picture and object there is usually a system of representation—a plan of correlation—under which the picture represents the object.*

For Goodman, realistic representation is a matter of convention; it "depends on how stereotyped the model of representation is, how commonplace the labels and their uses have become." Bieusheuvel (1947) expressed the same opinion: "The picture, particularly one printed on paper, is a highly conventional symbol, which the child reared in Western culture has learned to interpret." These statements, taken at face value, invalidate any meaningful basis for saying that a certain visualization is fundamentally better or more natural than another, for if even a realistic picture must be learned this would mean that all languages are equally valid in that all must be learned. If we accept this position, the best approach to designing visual languages would be to establish graphical conventions early and stick to them. It would not matter what the conventions were, only that we adhered to them in order to reduce the labor of learning new conventions.

In support of the nominalist argument, a number of anthropologists have reported expressions of puzzlement from people who encounter pictures for the first time. "A Bush Negro woman turned a photograph this way and that, in attempting to make sense out of the shadings of gray on the piece of paper she held" (Herskovits, 1948). The evidence related to whether or not we must learn to see pictures has been carefully reviewed and analyzed by Kennedy (1974). He rejected the strong position that pictures and other visual representations are entirely arbitrary. In the case of the reported puzzlement of people who are seeing pictures for the first time, Kennedy argued that these people are amazed by the technology rather than unable to interpret the picture. After all, a photograph is a remarkable artifact. What curious person would not turn it over to see if, perhaps, the reverse side contains some additional interesting information?

Here are two of the many studies that contradict the nominalist position and suggest that people can interpret pictures without training. Deregowski (1968) reported studies of adults and children in a remote area of Zambia who had very little graphic art. Despite this, these people could easily match photographs of toy animals with the actual toys. In an extraordinary but very different kind of experiment, Hochberg and Brooks (1962) raised their daughter nearly to the age of two in a house with no pictures. She was never read to from a picture book, and there were no pictures on the walls in the house. Although her parents could not completely block the child's exposure to pictures on trips outside the house, they were careful never to indicate a picture and tell the child that it was a representation of something. Thus, she had no social input telling her that pictures had any kind of meaning. When the child was finally tested she had a reasonably large vocabulary, and she was asked to identify objects in line drawings and in black-and-white photographs. Despite her lack of instruction in the interpretation of pictures, she was almost always correct in her answers, indicating that a basic understanding of pictures is not a learned skill.

Nevertheless, the issue of how pictures, especially line drawings, are able to unambiguously represent things is still not fully understood. Clearly, a portrait is a pattern

Figure 1.4 Two graphical methods for showing the same set of relationships between entities.

of marks on a page; in a physical sense, it is utterly unlike the flesh-and-blood person it depicts. The most probable explanation is that, at some stage in visual processing, the pictorial outline of an object and the object itself excite similar neural processes (Pearson et al., 1990). This view is made plausible by the ample evidence that one of the most important products of early visual processing is the extraction of linear features in the visual array. These may be either the visual boundaries of objects or the lines in a line drawing. The nature of these mechanisms is discussed further in Chapter 6.

When we turn to diagrams and non-pictorial visualizations, it is clear that convention must play a greater role. Figure 1.3(b) is not remotely "like" any scene in the real world under any system of measurement. Nevertheless, we can argue that many elements in it are constructed in ways that for perceptual reasons make the diagram easy to interpret. The lines that connect the various components, for example, are a notation that is easy to read, because the visual cortex of the brain contains mechanisms specifically designed to seek out continuous contours. Other possible graphical notations for showing connectivity would be far less effective. Figure 1.4 shows two different conventions for demonstrating relationships between entities. The connecting lines on the left are much more effective than the symbols on the right.

Sensory versus Arbitrary Symbols

In this book, the word *sensory* is used to refer to symbols and aspects of visualizations that derive their expressive power from their ability to use the perceptual processing power of the brain without learning. The word *arbitrary* is used to define aspects of representation that must be learned, because the representations have no perceptual basis. For example, the written word *dog* bears no perceptual relationship to any actual animal. Probably very few graphical languages consist of entirely arbitrary conventions, and probably none is entirely sensory; however, the sensory-versus-arbitrary distinction is important. If well designed, sensory representations are effective because they are well matched to the first stages of neural processing. They tend to be stable across individuals, cultures, and time. A circle represents a bounded region for everyone. Conversely, arbitrary conventions derive their power from culture and are therefore dependent on the particular cultural milieu of an individual.

The theory that a visual representation can be good or poor depending on how well it fits with visual processing is ultimately based on the idea that the human visual system has evolved as a specialized instrument to perceive the physical world. It rejects the idea that the visual system can adapt to any universe. It was once widely held that the brain at birth was an undifferentiated neural net, capable of configuring itself to perceive in any world, no matter how strange. According to this theory, if a newborn human infant were to be born into a world with entirely different rules for the propagation of light, that infant would nevertheless learn to see. Partly, this view came from the fact that all cortical brain tissue looks more or less the same, a uniform pinkish gray, so it was thought to be functionally undifferentiated. This *tabula rasa* view has been overthrown as neurologists have come to understand that the brain has a great many specialized regions. Figure 1.5 shows the major neural pathways between different parts of the brain involved in visual processing (Distler et al., 1993). Although

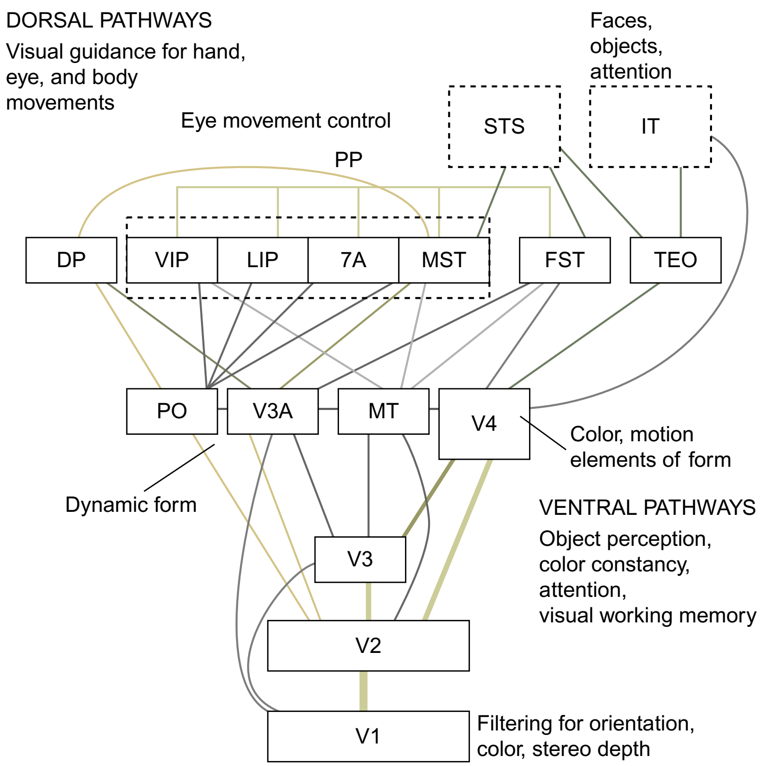

Figure 1.5 The major visual pathways of the Macaque monkey. This diagram is included to illustrate the structural complexity of the visual system and because a number of these areas are referenced in different sections of this book. V1 to V4, visual areas 1 to 4; PO, parietooccipital area; MT, middle temporal area; IT, inferotemporal cortex. (*Redrawn from Distler et al. (1993)*.)

much of the functionality remains unclear, this diagram represents an amazing achievement and summarizes the work of dozens of researchers. These structures are present in both higher primates and humans. The brain is clearly not an undifferentiated mass; it is more like a collection of highly specialized parallel processing machines with high-bandwidth interconnections. The entire system is designed to extract information from the world in which we live, not from some other environment with entirely different physical properties.

Certain basic elements are necessary for the visual system to develop normally; for example, cats reared in a world consisting only of vertical stripes develop distorted visual cortices, with an unusual preponderance of vertical-edge detectors. Nevertheless, the basic elements for the development of normal vision are present in all but the most abnormal circumstances. The interaction of the growing nervous system with everyday reality leads to a more or less standard visual system. This should not surprise us; the everyday world has ubiquitous properties that are common to all environments. All earthly environments consist of objects with well-defined surfaces, surface textures, surface colors, and a variety of shapes. Objects exhibit temporal persistence—they do not randomly appear and vanish, except when there are specific causes. At a more fundamental level, light travels in straight lines and reflects off surfaces in certain ways. The law of gravity continues to operate. Given these ubiquitous properties of the everyday world, the evidence suggests that we all develop essentially the same visual systems, irrespective of cultural milieu.

Monkeys and even cats have visual structures very similar to those of humans; for example, although Figure 1.5 is based on the visual pathways of the Macaque monkey, a number of lines of evidence show that the same structures exist in humans. First, the same areas can be identified anatomically in humans and animals. Second, specific patterns of blindness occur that point to the same areas having the same functions in humans and animals; for example, if the brain is injured in area V4, patients suffer from achromatopsia (Zeki, 1992; Milner & Goodale, 1995). These patients perceive only shades of gray, and they cannot recall colors from times before the lesion was formed. Color processing occurs in the same region of the monkey cortex. Third, new research imaging technologies, such as positron emission tomography (PET) and functional magnetic resonance imaging (fMRI), show that in response to colored or moving patterns the same areas are active in people as in the Macaque monkey (Zeki, 1992; Beardsley, 1997). The key implication of this is that, because we all have the same visual system, it is likely that we all see in the same way, at least as a first approximation. Hence, the same visual designs will be effective for all of us.

Sensory aspects of visualizations derive their expressive power from being well designed to stimulate the visual sensory system. In contrast, arbitrary, conventional aspects of visualizations derive their power from how well they are learned. Sensory and arbitrary representations differ radically in the ways they should be studied. In the former case, we can apply the full rigor of the experimental techniques developed by sensory neuroscience, while in the latter case visualizations and visual symbols can best be studied with the very different interpretive methodology, derived from the structuralist social sciences. With sensory representations, we can also make claims that transcend cultural and racial boundaries. Claims based on a generalized perceptual processing system will apply to all humans, with obvious exceptions such as color blindness.

This distinction between the sensory and social aspects of the symbols used in visualization also has practical consequences for research methodology. It is not worth expending a huge effort carrying out intricate and highly focused experiments to study something that is only this year's fashion; however, if we can develop generalizations that apply to large classes of visual representations, and for a long time, the effort is worthwhile. If we accept the distinction between sensory and arbitrary codes, we nevertheless must recognize that most visualizations are hybrids. In the obvious case, they contain both pictures and words, but in many cases the sensory and arbitrary aspects of a representation are much more difficult to tease apart. There is an intricate interweaving of learned conventions and hardwired processing. The distinction is not as clean as we would like, but there are ways of distinguishing the different kinds of codes.

Properties of Sensory Representation

The following paragraphs summarize some of the important properties of sensory representations:

> ***Understanding without training.*** A sensory code is one for which the meaning is perceived without additional training. Usually, all that is necessary is for the audience to understand that some communication is intended. For example, it is immediately clear that the image in Figure 1.6 has an unusual spiral structure. Even though this visually represents a physical process that cannot actually be seen, the detailed shape can be understood because it has been expressed using an artificial shading technique to make it look like a 3D solid object. Our visual systems are built to perceive the shapes of 3D surfaces.

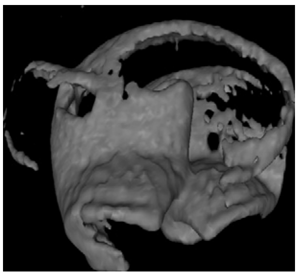

Figure 1.6 The expanding wavefront of a chemical reaction is visualized (Cross et al., 1997). Even though this process is alien to most of us, the shape of the structure is readily perceived.

Resistance to alternative denotation. Many sensory phenomena, such as the illusions shown in Figure 1.7, persist despite the knowledge that they are illusory. We can tell someone that the lines are the same length, but they will still seem to that person as different. When such illusions occur in diagrams, they are likely to be misleading. What is important to the present argument, though, is that some aspects of perception will be taken as facts that we contradict at our peril; for example, using connecting lines to denote that two objects are *not* (conceptually) connected would be a very bad idea, as it would contradict a deep perceptual metaphor.

Sensory immediacy. The processing of certain kinds of sensory information is hardwired and fast. We can represent information in certain ways that are neurally processed in parallel. This point is illustrated in Figure 1.8, which shows five different textured regions. The two regions on the left are very difficult to separate; the upright Ts and inverted Ts appear to be a single patch. The region of oblique Ts is easy to differentiate from the neighboring region of inverted Ts. The circles are the easiest to distinguish (Beck, 1966). The way in which the visual system divides the visual world into regions is called *segmentation*. The evidence suggests that this is a function of early rapid-processing systems. (Chapter 5 presents a theory of texture discrimination.)

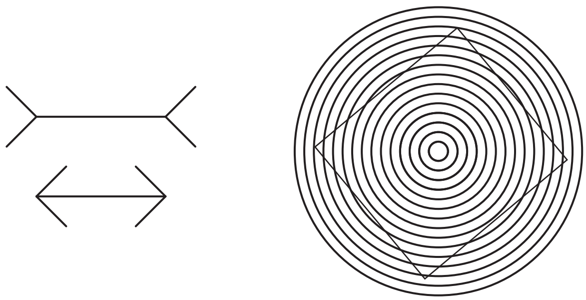

Figure 1.7 In the Muller–Lyer illusion on the left, the horizontal line in the upper figure appears longer than the one below. On the right, the rectangle appears distorted into a pincushion shape.

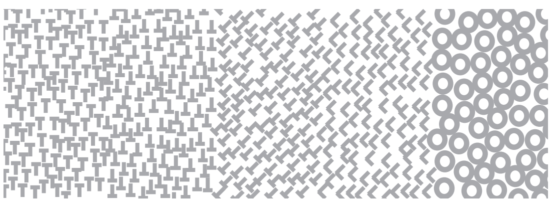

Figure 1.8 Five regions of texture. Some areas are easier to distinguish from others. (*Adapted from Beck (1966)*.)

> ***Cross-cultural validity.*** A sensory code will, in general, be understood across cultural boundaries. These may be national boundaries or the boundaries between different user groups. Instances in which a sensory code is misunderstood occur when some group has dictated that a sensory code be used arbitrarily in contradiction to the natural interpretation. In this case, the natural response to a particular pattern will, in fact, be wrong.

The foregoing analysis leads us to our first guideline.

> **[G1.1]** Design graphic representations of data by taking into account human sensory capabilities in such a way that important data elements and data patterns can be quickly perceived.

Exactly how this can be done is the subject of this book, but we will begin with two fundamental principles.

> **[G1.2]** Important data should be represented by graphical elements that are more visually distinct than those representing less important information.

Important information should be easy to find. The neural basis for visual search is now quite well understood, and as we shall see this allows us to determine with some precision which items are more findable than others.

> **[G1.3]** Greater numerical quantities should be represented by more distinct graphical elements.

This can be accomplished, for example, by making those elements, larger, more vividly colored, or more strongly textured. The basis for this claim is that even nonvisual thought as embodied in spoken and written language is grounded in sensory metaphors (Pinker, 2007).

Notice that guidelines G1.2 and G1.3 propose using the same kind of coding (visual distinctness) for different purposes, and this can lead to design conflicts. Also, sometimes a large quantity of something may not be especially important. Indeed, if we are running out of a critical asset (such as petroleum in the gas tank), we will want whatever represents this small quantity to be visually distinct. Ultimately, deciding how to use visual coding principles is a design issue. In any complex design problem, the optimal perceptually based coding solution may not be possible for each individual piece of information because some graphic resource (e.g., a bright color) may have already been used. It is only possible to provide perceptually based design guidelines for relatively simple situations. Where requirements are complex, it is the designer's task to make the right choices and use graphic resources wisely.

The solution in the gas tank problem, for example, can be something additional and very visually salient—a blinking light—to indicate the shortage of gas.

Testing Claims about Sensory Representations

Entirely different methodologies are appropriate to the study of representations of the sensory and arbitrary types. In general, the study of sensory representations can employ the scientific methods of vision researchers and biologists. The study of arbitrary conventional representations is best done using the techniques of the social sciences, such as sociology and anthropology; philosophers and cultural critics have much to contribute. Appendix C provides a brief summary of the research methodologies that apply to the study of sensory representations. All are based on the concept of the controlled experiment. For more detailed information on techniques used in vision research and human-factors engineering, see Palmer (1999) and Wickens (1992).

Representations That Are Arbitrary

One way of looking at the sensory-versus-arbitrary distinction is in terms of the time the two modes have taken to develop. Sensory codes are the products of the millions of years it has taken for our visual systems to evolve. The development of arbitrary conventional representations (such as number systems) occurred over the past thousands of years, but many more have had only a few decades of development. High-performance interactive computer graphics have greatly enhanced our capability to create new codes. We can now control motion and color with flexibility and precision. For this reason, we are currently witnessing an explosive growth in the invention of new graphic codes.

Arbitrary codes are by definition socially constructed. The word *dog* is meaningful because we all agree on its meaning and we teach our children the meaning. The word *carrot* would do just as well, except we have already agreed on a different meaning for that word. In this sense, words are arbitrary; they could be swapped and it would make no difference, as long as they are used consistently from the first time we encounter them. Arbitrary visual codes are often adopted when groups of scientists and engineers construct diagramming conventions for new problems that arise. Examples include circuit diagrams used in electronics, diagrams used to represent molecules in chemistry, and the unified modeling language used in software engineering. Of course, many designers will intuitively use perceptually valid forms in the codes, but many aspects of these diagrams are entirely conventional. Arbitrary codes have the following characteristics:

Hard to learn. It takes a child hundreds of hours to learn to read and write, even if the child has already acquired spoken language. The graphic codes of the alphabet and their rules of combination must be laboriously learned. The Chinese character set is reputed to be even harder to work with than the Roman.

Easy to forget. Arbitrary conventional information that is not overlearned can easily be forgotten. It is also the case that arbitrary codes can interfere with each other. In contrast, sensory codes cannot be forgotten.

Embedded in culture and applications. Different cultures have created their own distinctive symbol sets. An Asian student in my laboratory was working on an application to visualize changes in computer software. She chose to represent deleted entities with the color green and new entities with red. I suggested to her that red is normally used for a warning, while green symbolizes renewal, so perhaps the reverse coding would be more appropriate. She protested, explaining that green symbolizes death in China, while red symbolizes luck and good fortune.

Many graphical symbols are transient and tied to a local culture or application. Think of the graffiti of street culture or the hundreds of new graphical icons that are being created on the Internet. These tend to convey meaning with little or no syntax to bind the symbols into a formal structure. On the other hand, in some cases, arbitrary representations can be almost universal and have elaborate grammars associated with their use. The Arabic numerals shown in Figure 1.9 are used widely throughout the world. Even if a more perceptually valid code could be constructed, the effort would be wasted. The designer of a new symbology for Air Force or Navy charts must live within the confines of existing symbols because of the huge amount of effort invested in the standards. We have many standardized visualization techniques that work well and are solidly embedded in work practices, and attempts to change them would be foolish. In many applications, good design is standardized design.

Conventional symbol systems persist because they have become embedded in ways in which we think about problems. For many geologists, the topographic contour map is the ideal way to understand relevant features of the Earth's surface. They often resist shaded computer graphics representations, even though these appear to be much more intuitively understandable to most people. Contour maps are embedded in cartographic culture and training.

Formally powerful. Arbitrary graphical notations can be constructed that embody formally defined, powerful languages. Mathematicians have created hundreds of graphical languages to express and communicate their concepts. The expressive power of mathematics to convey abstract concepts in a formal, rigorous way is unparalleled; however, the languages of mathematics are extremely difficult to learn (at least for most people). Clearly, the fact that something is expressed in a visual code does not mean that it is easy to understand.

Figure 1.9 Two methods for representing the first five digits. The code given below is easier to learn but is not easily extended.

The foregoing analysis leads to our fourth guideline.

> **[G1.4]** Graphical symbol systems should be standardized within and across applications.

It is important, however, that they first be designed to be perceptually efficient.

The Study of Arbitrary Conventional Symbols

The appropriate methodology for studying arbitrary symbols is very different from that used to study sensory symbols. The tightly focused, narrow questions addressed by psychophysics are wholly inappropriate to investigating visualization in a cultural context. A more appropriate methodology for the researcher of arbitrary symbols may derive from the work of anthropologists such as Clifford Geertz (1973), who advocated "thick description." This approach is based on careful observation, immersion in culture, and an effort to keep "the analysis of social forms closely tied … to concrete social events and occasions." Also borrowing from the social sciences, Carroll and co-workers developed an approach to understanding complex user interfaces that they call *artifact analysis* (Carroll, 1989). In this approach, user interfaces (and presumably visualization techniques) are best viewed as artifacts and studied much as an anthropologist studies cultural artifacts of a religious or practical nature. Formal experiments are out of the question in such circumstances, and if they were actually carried out, they would undoubtedly change the very symbols being studied. Unfortunately for researchers, sensory and arbitrary aspects of symbols are closely intertwined in many representations, and although they have been presented here as distinct categories the boundary between them is very fuzzy. There is no doubt that culture influences cognition; it is also true that the more we know, the more we perceive. Pure instances of sensory or arbitrary coding may not exist, but this does not mean that the analysis is invalid. It simply means that for any given example we must be careful to determine which aspects of the visual coding belong in each category.

In general, our scientific understanding of how visualizations work is still in its infancy. There is much about visualization and visual communication that is more craft than science. For the visualization designer, training in art and design is at least as useful as training in perceptual psychology. For those who wish to do good design, the study of design by example is generally most appropriate, but the science of perception can provide a scientific basis for design rules, and it can suggest entirely new design ideas and methods for displaying data that have not been tried before.

Gibson's Affordance Theory

The great perception theorist J. J. Gibson brought about radical changes in how we think about perception with his theories of ecological optics, affordances, and direct perception. Aspects of each of these theoretical concepts are discussed throughout this book. We begin with affordance theory (Gibson, 1979).

Gibson argued that we perceive in order to operate on the environment. Perception is designed for action. Gibson called the perceivable possibilities for action *affordances*, and a cornerstone of his theory is that affordances are perceived in a *direct* and immediate way. They are not *inferred* from sensory clues. This theory is clearly attractive from the perspective of visualization, because the goal of most visualization is decision making. Thinking about perception in terms of action is likely to be much more useful than thinking about how two adjacent spots of light influence each other's appearance (which is the typical approach of classical psychophysicists). Much of Gibson's work was in direct opposition to the approach of theorists who reasoned that we must deal with perception from the bottom up, as with geometry. The pre-Gibsonian theorists tended to have an atomistic view of the world. They thought we should first understand how single points of light were perceived, and then we could work on understanding how pairs of lights interacted and gradually build up to understanding the vibrant, dynamic visual world in which we live. Gibson took a radically different, top-down approach. He claimed that we do not perceive points of light; rather, we perceive possibilities for action. We perceive surfaces for walking, handles for pulling, space for navigating, tools for manipulating, and so on.

In general, our whole evolution has been geared toward perceiving useful possibilities for action. In an experiment that supports this view, Warren (1984) showed that subjects were capable of accurate judgments of the "climbability" of staircases. These judgments depended on their own leg lengths. Gibson's affordance theory is tied to a theory of direct perception. He claimed that we perceive affordances of the environment directly and immediately, not indirectly by piecing together evidence from our senses.

Translating the affordance concept into the interface domain, we might construct the following principle: A good interface has affordances that make the user's task easy; for example, if we have a task of moving an object in 3D space, it should have clear handles to use in rotating and lifting the object. Figure 1.10 shows a design for

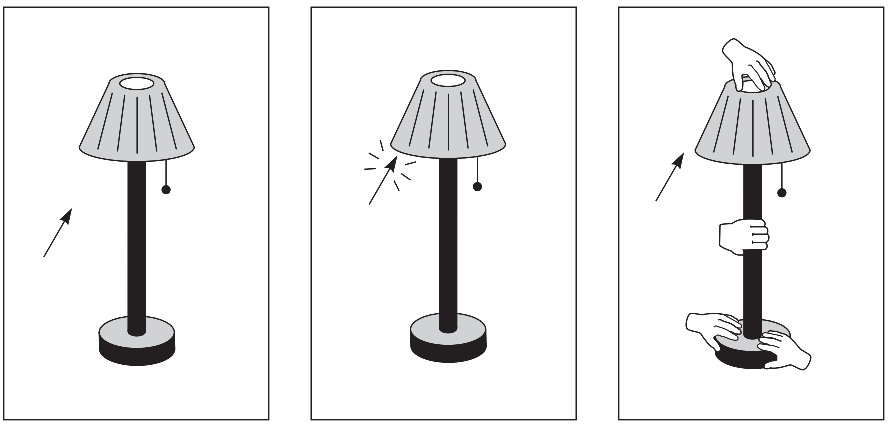

Figure 1.10 Cartoon cues are used to illustrate what interactions are possible. (*From Houde (1992). Reproduced with permission*.)

a 3D object manipulation interface from Houde (1992). When an object is selected, "handles" appear that allow the object to be lifted or rotated. The function of these handles is made more explicit by illustrations of gripping hands that show the affordances.

Gibson's theory, however, presents problems if it is taken literally. According to Gibson, affordances are physical properties of the environment that we directly perceive. Many theorists, unlike Gibson, think of perception as a very active process: The brain deduces certain things about the environment based on the available sensory evidence. Gibson rejected this view in favor of the idea that our visual system is tuned to perceiving the visual world and that we perceive it accurately except under extraordinary circumstances. He preferred to concentrate on the visual system as a whole and not to break perceptual processing down into components and operations. He used the term *resonating* to describe the way the visual system responds to properties of the environment. This view has been remarkably influential and has radically changed the way vision researchers think about perception; nevertheless, few would accept it today in its pure form.

There are three problems with Gibson's direct perception approach in developing theories of how visualizations work. The first problem is that even if perception of the environment is direct, it is clear that visualization of data through computer graphics is very indirect. Typically, there are many layers of processing between the data and its representation. In some cases, the source of the data may be microscopic or otherwise invisible. The source of the data may be quite abstract, such as company statistics in a stock-market database. Direct perception is not a meaningful concept in these cases.

Second, there are no clear physical affordances in any graphical user interface. To say that a screen button "affords" pressing in the same way as a flat surface affords walking is to stretch the theory beyond reasonable limits. In the first place, it is not even clear that a real-world button affords pressing. In another culture, these little bumps might be perceived as rather dull architectural decorations. Clearly, the use of buttons is arbitrary; we must learn that buttons, when pressed, do interesting things in the real world. Perception and action are linked in even more indirect ways when we use a computer; for instance, we must learn that a picture of a button can be "pressed" using a mouse, a cursor, or yet another button. This is far from being direct interaction with the physical world.

Third, Gibson's rejection of visual mechanisms is a problem. To take but one example, much that we know about color is based on years of experimentation, analysis, and modeling of the perceptual mechanisms. Color television and many other display technologies are based on an understanding of these mechanisms. To reject the importance of understanding visual mechanisms would be to reject most of vision research as irrelevant. This entire book is based on the premise that an understanding of perceptual mechanisms is basic to providing visualization designers with sound design principles.

Despite these reservations, Gibson's theories influence much of this book. The concept of affordances, loosely construed, can be extremely useful from a design perspective. The idea suggests that we build interfaces that beg to be operated in appropriate and useful ways. We should make virtual handles for turning, virtual buttons for pressing. If components are designed to work together, this should be made perceptually evident, perhaps by creating shaped sockets that afford the attachment of one object to another. This is the kind of design approach advocated by Norman in his famous book, *The Psychology of Everyday Things* (1988). Nevertheless, on-screen widgets present affordances only in an indirect sense. They borrow their power from our ability to represent pictorially, or otherwise, the affordances of the everyday world. Therefore, we can be inspired by affordance theory to produce good designs, but we cannot expect much help from that theory in building an applied science of visualization.

A Model of Perceptual Processing

In this section, we introduce a simplified information processing model of human visual perception. As Figure 1.5 shows, there are many subsystems in vision, and we should always be wary of overgeneralization. Still, an overall conceptual framework is useful in providing a starting point for more detailed analysis. Figure 1.11 gives a broad schematic overview of a three-stage model of perception. In Stage 1, information is processed in parallel to extract basic features of the environment.

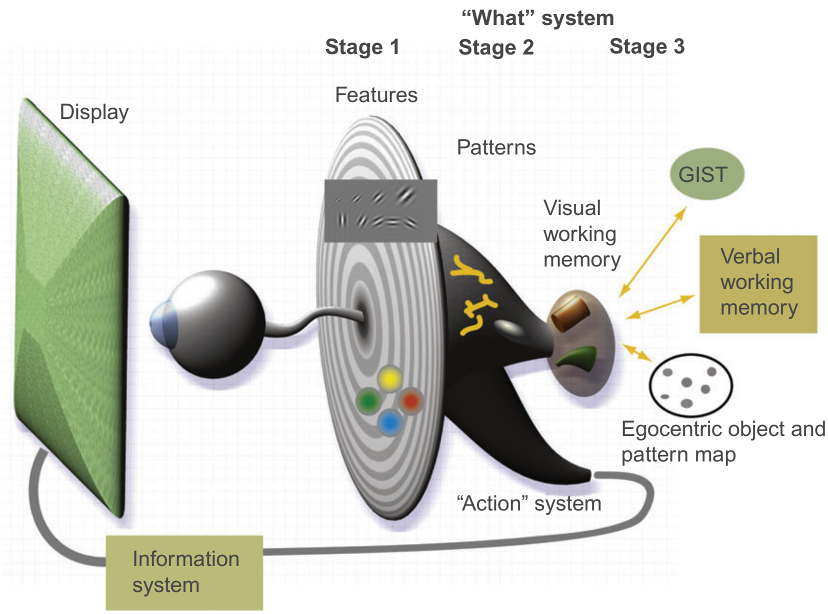

Figure 1.11 A three-stage model of visual information processing.

In Stage 2, active processes of pattern perception pull out structures and segment the visual scene into regions of different color, texture, and motion patterns. In Stage 3, the information is reduced to only a few objects held in visual working memory by active mechanisms of attention to form the basis of visual thinking.

Stage 1. Parallel Processing to Extract Low-Level Properties of the Visual Scene

Visual information is first processed by large arrays of neurons in the eye and in the primary visual cortex at the back of the brain. Individual neurons are selectively tuned to certain kinds of information, such as the orientation of edges or the color of a patch of light. In Stage 1 processing, billions of neurons work in parallel, extracting features from every part of the visual field simultaneously. Treisman (1985) described the result as a set of feature maps. This parallel processing proceeds whether we like it or not and is largely independent of what we choose to attend to (although not where we look). It is also rapid. If we want people to understand information quickly, we should present it in such a way that it can be easily detected by these large, fast computational systems in the brain. Important characteristics of Stage 1 processing include:

- Rapid parallel processing
- Extraction of features, orientation, color, texture, and movement patterns
- Transitory nature of information, which is briefly held in an iconic store
- Bottom-up, data-driven model of processing
- Serving as the basis for understanding the visual salience of elements in displays

Stage 2. Pattern Perception

At the second stage of visual analysis, rapid active processes divide the visual field into regions and simple patterns, such as continuous contours, regions of the same color, and regions of the same texture. Patterns of motion are also very important, although the use of motion as an information code is relatively neglected in visualization. The pattern-finding stage of visual processing is extremely flexible, influenced both by the massive amount of information available from Stage 1 parallel processing and by the top-down action of attention driven by visual queries. Marr (1982) called this stage of processing the *2-1/2D sketch*. Rensink (2002) called it a *proto-object flux* to emphasize its dynamic nature. Important characteristics of Stage 2 processing include:

- Slower serial processing
- Top-down attention being critical to the formation of objects and patterns pulled out from the feature maps

- A small number (one to three) patterns becoming "bound" and held for a second or two under top-down attentional processes
- Different pathways for object recognition and visually guided hand motion (the perception and action channels)

There is a major fork in the pattern-processing pathway, with one branch leading to object perception and the other branch leading to parts of the brain involved in the control of actions. This is the basis for the two-visual-system theory: one system for locomotion and action, called the *action system*, and another for object identification, called the *what system*. A detailed and convincing account of it can be found in Milner and Goodale (1995).

Stage 3. Visual Working Memory

At the highest level of perception are the objects held in visual working memory by the demands of active attention. In order to use an external visualization, we construct a sequence of visual queries that are answered through visual search strategies. At this level, only a few objects can be held at a time; they are constructed from the available patterns that may provide answers to the visual query and from information stored in long-term memory related to the task. For example, if we use a road map to look for a route, the visual query will trigger a search for connected red contours (representing major highways) between two visual symbols (representing cities).

Attention

Describing the visual system as a set of processing stages implies that visual information flows only from Stage 1 through Stage 2 to Stage 3. When a *new* image flashes on the screen in front of our eyes, or we make an eye movement to a part of the world we have not seen before, this is the only way information can flow. But, immediately following the upflow of information there is a top-down signal that consolidates and enhances what is happening at earlier stages. The entire system is being constantly tuned from top to bottom based on our expectations and on what will be most useful to us.

The generic name for this is *attention*. Attention is a multifaceted pervasive set of processes involving the entire visual system. Even the Stage 1 feature maps are subject to attention being tuned to be more sensitive to what we need to find. The Stage 2 patterns are the very essence of attention, and where our brains direct our eyes to move determines what will become the focus of our attention in the next instant. Eye movements are literally acts of reallocation of attention.

One of the more radical ideas in this book is that the effects of attention can be propagated outside of the brain into the world through cleverly designed interactive visualizations that cause information we are interested in to be highlighted on the screen.

Beyond the visual processing stages shown in Figure 1.11 are interfaces to other subsystems. The visual object identification process interfaces with the verbal linguistic subsystems of the brain so that words can be connected to images. The action system interfaces with the motor systems that control muscle movements.

The three-stage model of perception is the basis for the organization of the first seven chapters of this book. We work our way up from early to late stages of processing. Later chapters are more concerned with the system as a whole and the way visual thinking occurs as a process. The later chapters also discuss the interfaces between perceptual and other cognitive processes, such as those involved in language and decision making.

Costs and Benefits of Visualization

The ultimate goal of interactive visualization design is to optimize applications so that they help us perform cognitive work more efficiently. Optimizing a system requires that we have at least some conception of value. We use visualizations because they help us solve problems faster or better, or they let us learn something new, and these activities usually have monetary value. The following analysis is based in part on an economic model of the value of visualizations carried out by Jarke van Wijk (2006), but it differs in some important respects. Where van Wijk took *knowledge gain* to be the value of visualization we shall use the broader concept of *cognitive work*, as visualization can help us with many routine tasks: Executing trades on the stock market, cooking with a recipe, and working a cash register all involve cognitive work, part of which may be achieved through a form of visual thinking. The cash register in a fast-food restaurant has many specialized buttons relating to distinct combinations of fried potatoes, drinks, and different types of sandwiches. With the right layout and graphic design, a worker will process orders more rapidly with less training. At the other end of the spectrum is a major scientific discovery arising through the use of a visualization tool. In either case, the cognitive work has monetary value. This is not to deny that sometimes we pursue knowledge for its own sake and that it can be extremely difficult to place a value on a particular insight. But, if we are to compare the costs of producing a visual thinking tool with the value of using it, then we must use the same units on both sides of the equation and money is the obvious token of value. Because it is so difficult to quantify the value of knowledge, a highly detailed analysis is pointless—why add variables that we cannot quantify? Nevertheless, there are useful insights to be gained from first-order approximations.

A visualization can be viewed from two important perspectives: the perspective of the developer and the perspective of the user. We begin with the user. In the following, the * symbol is used to denote multiplication.

The basic user costs are

$$(\textit{The time to learn to use the visualization} * \textit{the value of the user's time}) + \\ (\textit{the time spent carrying out the work} * \textit{the value of the user's time})$$

The user benefits are

$$\textit{The cognitive work done} * \textit{the value of the work}$$

There are some straightforward implications of this.

> **[G1.5]** Where two or more tools can perform the same task, choose the one that allows for the most valuable work to be done per unit time.

This rather obvious guideline is the basis for much of the content of this book, because in many cases we will be considering alternative visual representations of the same data for the same purpose. Efficient visualizations allow people to find important patterns faster and thereby perform work in less time.

> **[G1.6]** Consider adopting novel design solutions only when the estimated payoff is substantially greater than the cost of learning to use them.

Learning to interpret a novel data representation or a novel mode of interaction can require a significant effort. It is often not worth learning a new tool, especially if the number of times it will be used is uncertain.

People use a variety of different thinking tools that are inconsistent with one another in the sense that operations must be carried out with different commands and the same data types are represented using different visual symbols. There is a cognitive cost to this, both in learning and continuous use. Perhaps different symbols are used to represent the same piece of information.

> **[G1.7]** Unless the benefit of novelty outweighs the cost of inconsistency, adopt tools that are consistent with other commonly used tools.

This guideline can be extremely frustrating for the designer of innovative solutions. It often means that something that seems to be clearly and measurably superior when viewed in isolation is in fact not useful overall.

Now look at the developer side of the ledger.

The basic developer costs are

$$\begin{aligned}&\textit{The cost to design and implement a cognitive tool} + \textit{the cost to market} +\\&\quad \textit{the cost to manufacture} + \textit{the cost to service}\end{aligned}$$

The developer benefits are

$$\begin{aligned}&(\textit{The number of units sold} * \textit{the price per unit}) +\\&\qquad \textit{the revenue from maintenance contracts}\end{aligned}$$

With computer software, manufacturing costs are essentially zero and the cost to service is typically covered by maintenance. Profit can be approximated as follows:

$$\textit{Profit} = (\textit{Units sold} * \textit{price}) - (\textit{cost to create} + \textit{cost to market})$$

Significant revenue can come by selling a lot of cheap things or selling a few expensive ones. Examples of high-volume visualizations are the weather maps used by millions of people every day. Examples of customized, high-value visualizations are the tools used to control spacecraft. Because tool developers are interested in profiting from their efforts, the amount of design effort should be related to the anticipated payoff.

> **[G1.8]** Effort spent on developing tools should be in proportion to the profits they are expected to generate. This means that small-market custom solutions should be developed only for high-value cognitive work.

It must be recognized that this simple profit model often does not apply because many people who generate visualizations are academics not motivated by profit or even by the goal of increasing the efficiency of cognitive work. To the academic, for the most part, value is not based on monetary return; instead, it is based on published ideas. Published academic papers result in job tenure, increased recognition, and ultimately greater salary. Although this suggests an ultimate financial motive, novelty and a certain level of sophistication are more important requirements for getting a paper published, as opposed to whether a method is actually superior. The academic approach often results in methods that are not valuable, but sometimes it results in inventions that a more commercial approach would never discover.

Types of Data

If the goal of visualization research is to transform data into a perceptually efficient visual format, and if we are to make statements with some generality, we must be able to say something about the types of data that can exist for us to visualize. It is useful, but less than satisfying, to be able to say that color coding is good for stock-market symbols but texture coding is good for geological maps. It is far more useful to be able to define broader categories of information, such as continuous quantity maps (scalar fields), continuous flow fields (vector maps), and category data, and then to make general statements such as "Color coding is good for category information" and "Motion coding is good for highlighting selected data." If we can give perceptual reasons for these generalities, we have an applied science of visualization.

Unfortunately, the classification of data is a big issue. It is closely related to the classification of knowledge, and it is with great trepidation that we approach the subject. What follows is an informal classification of data classes using a number of concepts that we will find helpful in later chapters. We make no claims that this classification is especially profound or all encompassing.

Bertin (1977) suggested that there are two fundamental forms of data: data values and data structures. A similar idea is to divide data into entities and relationships (often called *relations*). Entities are the objects we wish to visualize; relations define the structures and patterns that relate entities to one another. Sometimes the relationships are provided explicitly; sometimes discovering relationships is the very purpose of visualization. We can also talk about the attributes of an entity or a relationship; for example, an apple can have color as one of its attributes. The concepts of entity, relationship, and attribute have a long history in database design and have been adopted more recently in systems modeling; however, we shall extend these concepts beyond the kinds of data that are traditionally stored in a relational database. In visualization, it is necessary to deal with entities that are more complex, and we are also interested in seeing complex structured relationships—data structures—not captured by the entity relationship model.

Entities

Entities are generally the objects of interest. People can be entities; hurricanes can be entities. Both fish and fishponds can be entities. A group of things can be considered a single entity if it is convenient—for example, a school of fish.

Relationships

Relationships form the structures that relate entities. There can be many kinds of relationships. A wheel has a "part-of" relationship to a car. One employee of a firm may have a supervisory relationship to another employee. Relationships can be structural and physical, as in defining the way a house is made of its many component parts, or they can be conceptual, as in defining the relationship between a store and its customers. Relationships can be causal, as when one event causes another, and they can be purely temporal, defining an interval between two events.

Attributes of Entities or Relationships

Both entities and relationships can have attributes. In general, something should be called an attribute (as opposed to an entity itself) when it is a property of some entity and cannot be thought of independently. Thus, the color of an apple is an attribute of the apple. The temperature of water is an attribute of the water. Duration is an attribute of a journey. Defining what should be an entity and what should be an attribute is not always straightforward. The salary of an employee, for example, could be thought of as an attribute of the employee, but we can also think of an amount of money as an entity unto itself, in which case we would have to define a relationship between the employee entity and the sum-of-money entity.

Data Dimensions: 1D, 2D, 3D, …

An attribute of an entity can have multiple dimensions. We can have a single scalar quantity, such as the weight of a person. We can have a vector quantity, such as the direction in which that person is traveling. Tensors are higher-order quantities that describe both direction and shear forces, such as occur in materials that are being stressed. We can have a field of scalars, vectors, or tensors. The gravitational field of the Earth is a three-dimensional attribute of the Earth. In fact, it is a three-dimensional vector field attribute. If we are interested only in the strength of gravity at the Earth's surface, it is a two-dimensional scalar attribute. Often, the term *map* is used to describe this kind of field; thus, we talk about a gravity map or a temperature map.

Types of Numbers

It is often desirable to describe data visualization methods in light of the quality of attributes they are capable of conveying. A useful way to consider the quality of data is the taxonomy of number scales defined by the statistician Stevens (1946). According to Stevens, there are four levels of measurement: nominal, ordinal, interval, and ratio scales:

> ***Nominal.*** This is the labeling function. Fruit can be classified into apples, oranges, bananas, and so on. There is no sense in which the fruit can be placed in an ordered sequence. Sometimes numbers are used in this way; for example, the number on the front of a bus generally has a purely nominal value. It identifies the route on which the bus travels.
>
> ***Ordinal.*** The ordinal category encompasses numbers used for ordering things in a sequence. It is possible to say that a certain item comes before or after another item. The position of an item in a queue or list is an ordinal quality. When we ask people to rank some group of things (films, political candidates, computers) in order of preference, we are requiring them to create an ordinal scale.
>
> ***Interval.*** When we have an interval scale of measurement, it becomes possible to derive the gap between data values. The time of departure and the time of arrival of an aircraft are defined on an interval scale.
>
> ***Ratio.*** With a ratio scale, we have the full expressive power of a real number. We can make statements such as "Object A is twice as large as object B." The mass of an object is defined on a ratio scale. Money is defined on a ratio scale. The use of a ratio scale implies a zero value used as a reference.

In practice, only three of Stevens's levels of measurement are widely used, and these in somewhat different form. The typical basic data classes most often considered in visualization have been greatly influenced by the demands of computer programming. They are the following:

> ***Category data.*** This is like Stevens's nominal class.
>
> ***Integer data.*** This is like his ordinal class in that it is discrete and ordered.
>
> ***Real-number data.*** This combines the properties of interval and ratio scales.

Uncertainty

In science and engineering it is common to attach an uncertainty attribute either to raw data or to derived data. Estimating uncertainty is a major part of engineering practice, and showing uncertainty in a visualization is important, although difficult to achieve. The problem is that once data is represented as a visual object, it attains a kind of literal concrete quality that makes the viewer think it is accurate.

Operations Considered as Data

An entity relationship model can be used to describe most kinds of data; however, it does not capture the operations that may be performed on entities and relationships. We tend to think of operations as somehow different from the data itself, neither entities nor relationships nor attributes. The following are a few common operations:

- Mathematical operations on numbers—multiplication, division, and so on
- Merging two lists to create a longer list
- Inverting a value to create its opposite
- Bringing an entity or relationship into existence (such as the mean of a set of numbers)
- Deleting an entity or relationship (a marriage breaks up)
- Transforming an entity in some way (the chrysalis turns into a butterfly)
- Forming a new object out of other objects (a pie is baked from apples and pastry)
- Splitting a single entity into its component parts (a machine is disassembled)

In some cases, these operations can themselves form a kind of data that we may wish to capture. Chemistry contains a huge catalog of the compounds that result when certain operations are applied to combinations of other compounds. These operations may form part of the data that is stored. Certain operations are easy to visualize; for example, the merging of two entities can easily be represented by showing two visual objects that combine (visually merge) into a single entity. Other operations are not at all easy to represent in any visualization; for example, the detailed logical structure of a computer program may be better represented using a written code that has its basis in natural language than using any kind of diagram. What should and should not be visualized is a major topic in Chapter 9.

Operations and procedures often present a particularly difficult challenge for visualization. It is difficult to express operations effectively in a static diagram, and this is especially a problem in the creation of visual languages. On the other hand, the use of animation opens up the possibility of expressing at least certain operations in an immediately accessible visual manner. We shall deal with the issue of animation and visual languages in Chapter 9.

Metadata

Metadata is data about data—who collected it, what transformations it has been subjected to, what is its uncertainty. When we are striving to understand data, certain products are sure to emerge as we proceed. We may discover correlations between variables or clusters of data values. We may postulate certain underlying mechanisms that are not immediately visible. The result is that theoretical entities come into being. Atoms, photons, black holes, and all the basic constructs of physics are like this. As more evidence accumulates, the theoretical entities seem more and more real, but they are nonetheless only observable in the most indirect ways. Metadata can be of any kind. It can consist of new entities, such as identified classes of objects, or new relationships, such as postulated interactions between different entities, or new rules. We may impose complex structural relationships on the data, such as tree structures or directed acyclic graphs, or we may find that they already exist in the data.

The visualization of metadata presents the same kinds of challenges as the visualization of non-metadata, as metadata consists ultimately of entities and relationships and of different kinds of numbers from nominal to real, and metadata may have a complex structure. Graphically representing metadata can be very challenging because it inevitably adds complexity, but the problems of representation are essentially the same. For this reason, metadata visualization is not discussed as a separate topic in this book.

Conclusion

Visualization applies vision research to practical problems of data analysis in much the same way as engineering applies physics to practical problems of building factories. Just as engineering has influenced physicists to become more concerned with areas such as semiconductor technology, so we may hope that the development of an applied science of data visualization can encourage vision researchers to intensify their efforts in addressing such problems as 3D space and task-oriented perception. There is considerable practical benefit in understanding these things. As the importance of visualization grows, so do the benefits of a scientific approach, but there is no time left to lose. New symbol systems are being developed constantly to meet the needs of a society increasingly dependent on data. Once developed, they may stay with us for a very long time, so we should try to get them right.

We have introduced a key distinction between the ideas of sensory and arbitrary conventional symbols. This is a difficult and sometimes artificial distinction. Nonetheless, the distinction is essential. Were there no basic model of visual processing to support the idea of a good data representation, all visual representations would be arbitrary, and ultimately the problem of visualization would come down to establishing consistent notations.

In opposition to the view that consistency is the only important criterion, this book takes the view that all humans have more or less the same visual system. This visual system has evolved over tens of millions of years to enable creatures to perceive and act within the natural environment. Although very flexible, the visual system is tuned to receiving data presented in certain ways, but not in others. If we can understand how the mechanism works, we can produce better displays and better thinking tools.

CHAPTER TWO

The Environment, Optics, Resolution, and the Display

We can think of the world itself as an information display. Each object by its shape suggests uses, such as a tool or construction material, or it may be seen as an obstacle to be avoided. Every intricate surface reveals the properties of the material from which it is made. Creatures signal their intentions inadvertently or deliberately through movement. There are almost infinite levels of detail in nature, and we must be responsive to both small and large things, but in different ways: Large things, such as logs, may be seats or tables; smaller things, such as hand-sized rocks, can be used as tools; still smaller things, such as grains of sand, are useful by the handful. In an evolutionary sense, our visual system is designed to extract useful information from the environment, and lessons from this can lead to the design of better visualizations.

The visual display of a computer is only a single rectangular planar surface, divided into a regular grid of small colored dots. It is astonishing how successful it is as an information display, given how little it resembles the world we live in. This chapter concerns the lessons we can learn about information display by appreciating the environment in broad terms and how the same kind of information can be picked up from a flat screen. It begins with a discussion of the most general properties of the visual environment and then considers the lens and receptor system of the eye as the principal instrument of vision. Later, the basic abilities of the eye are applied in an analysis of problems inherent in creating optimal display devices.

This level of analysis bears on a number of display problems. If we want to make virtual objects seem real, how should we simulate the interaction of light with their surfaces? What is the optimal display device and how do current display devices

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measure up? How much detail can we see? How faint a target can we see? How good is the lens system of the human eye? This is a foundation chapter, introducing much of the basic vocabulary of vision research.

The Environment

A strategy for designing a visualization is to transform the data so that it appears like a common environment—a kind of data landscape. We should then be able to transfer skills obtained in interpreting the real environment to understanding our data. This is not to say that we should represent data by means of synthetic trees, flowers, and undulating lawns—that would be quaint and ludicrous. It seems less ludicrous to create synthetic offices, with desks, filing cabinets, phones, books, and Rolodexes, and this is already being done in a number of computer interfaces. But, still, the space efficiency of these designs is poor; better methods exist, and understanding the properties of the environment is important for a more basic reason than simple imitation.

When trying to understand perception, it is always useful to think about what perception is for. The theory of evolution tells us that the visual system must have survival value, and adopting this perspective allows us to understand visual mechanisms in the broader context of useful skills, such as navigation, food seeking (which is an optimization problem like information seeking), and tool use (which depends on object-shape perception).

What follows is a short tour of the visual environment, beginning with light.

Visible Light

Perception is about understanding patterns of light. Visible light constitutes a very small part of the electromagnetic spectrum, as is shown in Figure 2.1. Some animals, such as snakes, can see in the infrared, while certain insects can see in the ultraviolet. Humans can perceive light only in the range of 400 to 700 nanometers. (In vision research, wavelength is generally expressed in units of 10^{-9} meters, called *nanometers*). At wavelengths shorter than 400 nm are ultraviolet light and X-rays. At wavelengths longer than 700 nm are infrared light, microwaves, and radio waves.

Ecological Optics

The most useful broad framework for describing the visual environment is given by *ecological optics*, a discipline developed by J. J. Gibson. Gibson radically changed the way we think about perception of the visual world. Instead of concentrating on the image on the retina, as did other vision researchers, Gibson emphasized perception of surfaces in the environment. The following quotations strikingly illustrate how he broke with a traditional approach to space perception that was grounded in the classical geometry of points, lines, and planes (Gibson, 1979):

> *A surface is substantial; a plane is not. A surface is textured; a plane is not. A surface is never perfectly transparent; a plane is. A surface can be seen; a plane can only be visualized.*

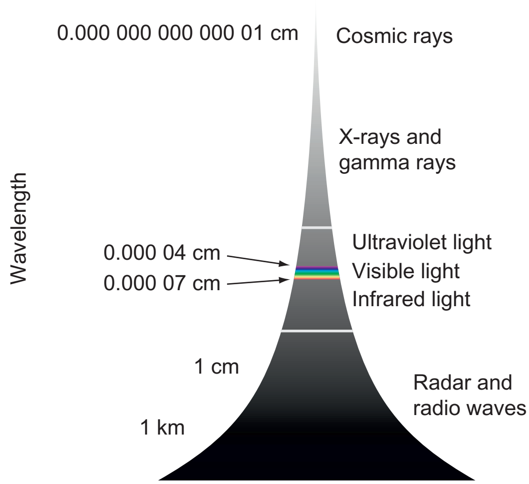


Figure 2.1 The visible light spectrum is a tiny part of a much larger spectrum of electromagnetic radiation.

> *A fiber is an elongated object of small diameter, such as a wire or thread. A fiber should not be confused with a geometrical line.*
> *In surface geometry the junction of two flat surfaces is either an edge or a corner; in abstract geometry the intersection of two planes is a line.*

Much of human visual processing becomes more understandable if we assume that a key function of the visual system is to extract properties of surfaces. As our primary interface with objects, surfaces are essential to understanding the potential for interaction and manipulation in the environment that Gibson called *affordances* (discussed in Chapter 1).

A second key concept in Gibson's ecological optics is the ambient optical array (Gibson, 1986). To understand the ambient optical array, consider what happens to light entering the environment from some source such as the sun. It is absorbed, reflected, refracted, and diffracted as it interacts with various objects such as stones, grass, trees, and water. The environment, considered in this way, is a hugely complex matrix with photons traveling in all directions, consisting of different mixtures of wavelengths and polarized in various ways. This complexity is impossible to simulate; however, from any particular stationary point in the environment, critical information is contained in the structure of the light arriving at that point. This vast simplification is what Gibson called the *ambient optical array*. This array encompasses all the rays arriving at a particular point as they are structured in both space and time. Figure 2.2 is intended to capture the flavor of the concept.

Much of the effort of computer graphics can be characterized as an attempt to model the ambient optical array. Because the interactions of light with surfaces are vastly complex, it is not possible to directly model entire environments, but the ambient

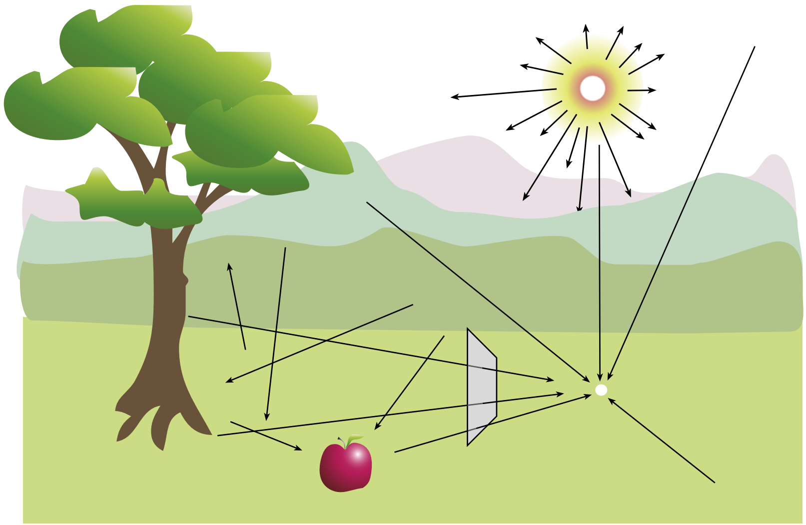


Figure 2.2 *Ambient optical array* is a term that describes the spherical array of light arriving from all directions at some designated point in the environment. Simulating the colors of the subset of rays that would pass through a glass rectangle is one of the main goals of computer graphics.

array provides the basis for simplifications such as those used in ray tracing so that approximations can be computed. If we can capture the structure of a bundle of rays passing through a glass rectangle on their way to the stationary point, we have something that we may be able to reproduce on a screen (see Figure 2.2).

Optical Flow

The ambient optical array is dynamic, changing over time both as the viewpoint moves and as objects move. As we advance into a static environment, a characteristic visual flow field develops. Figure 2.3 illustrates the visual field expanding outward as a result of forward motion. There is evidence that the visual system contains processes to interpret such flow patterns and that they are important in understanding how animals (including humans) navigate through space, avoid obstacles, and generally perceive the layout of objects in the world. The flow pattern in Figure 2.3 is only a very simple case; if we follow something with our eyes while we move forward, the pattern becomes more complex. The perceptual mechanisms to interpret flow patterns must therefore be sophisticated. The key point here is that visual images of the world are dynamic, so that the perception of motion patterns may be as important as the perception of the static world, albeit less well understood. Chapter 7 deals with motion perception in the context of space perception and three-dimensional (3D) information display.

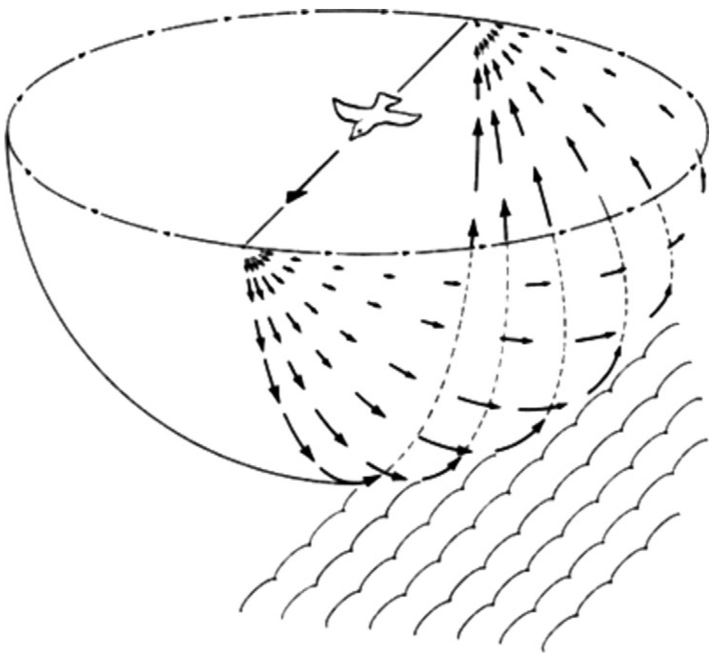


Figure 2.3 An expanding flow pattern of visual information is created as an observer moves while gazing in a forward direction. (*From Gibson (1979). Reproduced with permission.*)

Textured Surfaces and Texture Gradients

Gibson pointed out that surface texture is one of the fundamental visual properties of an object. In visual terms, a surface is merely an unformed patch of light unless it is textured. Texture is critical to perception in a number of ways. The texture of an object helps us see where an object is and what shape it has. On a larger scale, the texture of the ground plane on which we walk, run, and crawl is important in judging distances and other aspects of space. Figure 2.4 shows that the texture of the ground plane produces a characteristic texture gradient that is important in space perception. Of course, surfaces themselves are infinitely varied. The surface of a wooden table is very different from the surface of an ocelot. Generally speaking, most surfaces have clearly defined boundaries; diffuse, cloudlike objects are exceptional. Perhaps because of this, we have great difficulty in visualizing uncertain data as fuzzy clouds of points. At present, most computerized visualizations present objects as smooth and untextured. This may be partly because texturing is not yet easy to do in most visualization software packages and computer screens lack the resolution to display fine textures. Perhaps visualization designers have avoided texturing surfaces by applying the general esthetic principle that we should avoid irrelevant decoration in displays—"chart junk," to use Edward Tufte's memorable phrase (Tufte, 1983), but texturing surfaces is not chart junk, especially in 3D visualizations. Even if we texture all objects in

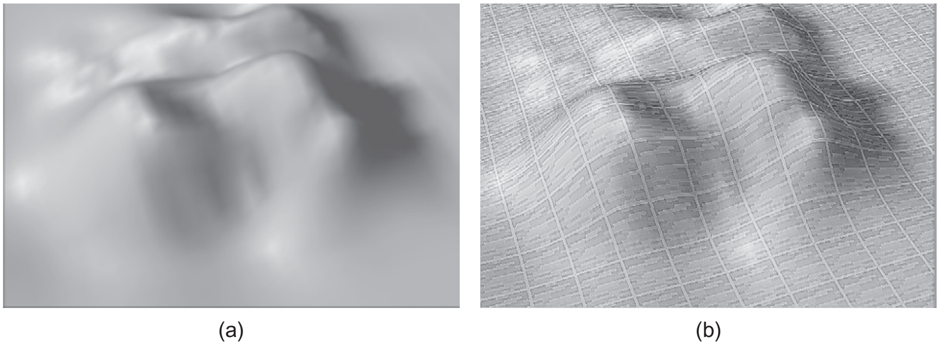


Figure 2.4 An undulating surface with (a) and without (b) surface texture.

exactly the same way, this can help us perceive the orientation, shape, and spatial layout of a surface. Textures need not be garish or obtrusive, but when we want something to appear to be a 3D surface, it should have at least a subtle texture. As we shall see in Chapter 6, texture can also be used to code information, but using unobtrusive textures will require better pixel resolution than is available on most displays.

The Paint Model of Surfaces

Surfaces in nature are endlessly varied and complex. Microtextures give irregular patterns of reflection, so the amount and color of reflected light can vary with both the illumination angle and the viewing angle. However, there is a simple model that approximates many common materials. This model can be understood by considering a glossy paint. The paint has pigment particles embedded in a more or less clear medium, as shown in Figure 2.5. Some of the light is reflected from the surface of the glossy medium and is unchanged in color. Most of the light penetrates the medium and is selectively absorbed by the pigment particles, altering its color. According to this model, there are three important direct interactions of light with surfaces, as described in the following paragraphs. An additional fourth property is related to the fact that parts of objects cast shadows, revealing more information about their shapes (see Figure 2.6).

- ***Lambertian shading.*** With most materials, light penetrates the surface and interacts with the pigment in the medium. This light is selectively absorbed and reflected depending on the color of the pigment, and some of it is scattered back through the surface out into the environment. If we have a perfectly matte surface, how bright the surface appears depends only on the cosine of the angle between the incident light and the surface normal. This is called the *Lambertian model*, and although few real-world materials have exactly this property it is computationally very simple. A patch of a Lambertian surface can be viewed from any angle and the surface color will seem the same. Figure 2.6(a) shows a surface with only Lambertian shading. Lambertian shading is the simplest method for representing surface shape from shading. It can also be highly effective.

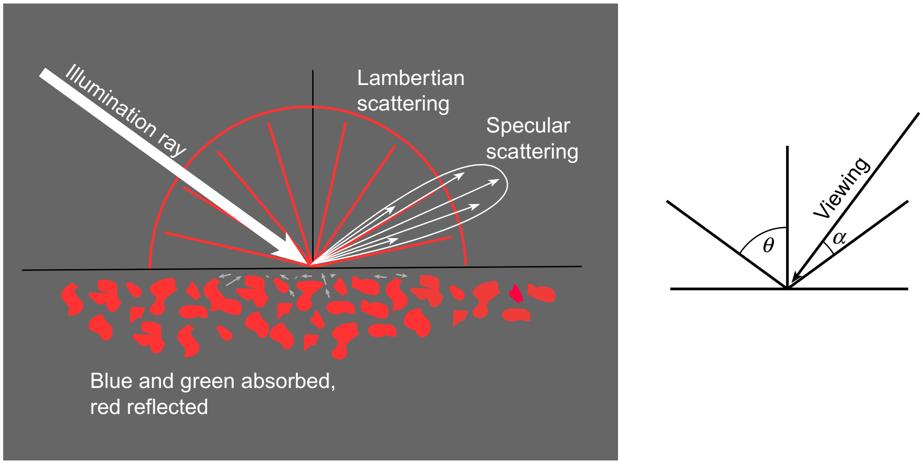
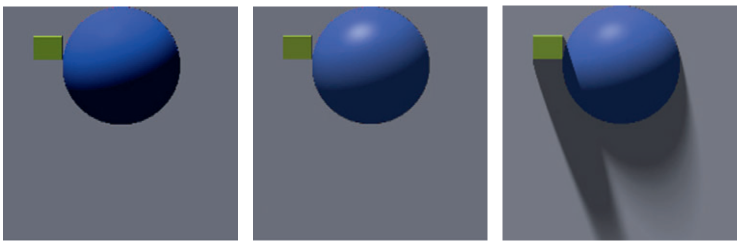


Figure 2.5 This simplified model of light interacting with surfaces is used in most computer graphics. Specular reflection is light that is reflected directly from the surface without penetrating into the underlying pigment layer.



(a) (b) (c)

Figure 2.6 (a) Lambertian shading only. (b) Lambertian shading with specular and ambient shading. (c) Lambertian shading with specular, ambient, and cast shadows.

- ***Specular shading.*** The light that is reflected directly from a surface is called *specular*. This is what we see as the highlights on glossy objects. Specular reflection obeys the optical principle of mirror reflection: The angle of reflection equals the angle of incidence. It is possible to simulate high-gloss, semigloss, or eggshell finishes by causing the specular light to spread out somewhat, simulating different degrees of roughness at a microscopic level. Specular light reflected from a surface retains the color of the illuminant; it is not affected by the color of the underlying pigment. Hence, we see white highlights gleaming from the surface of a red automobile. Specular reflection depends on the viewpoint, unlike Lambertian reflection; both the viewing direction and the positions of the light sources affect the locations where highlights appear. Figure 2.6(b) shows a surface with both Lambertian and specular shading.

- ***Ambient shading.*** Ambient light is the light that illuminates a surface from everywhere in the environment, except for the actual light sources. In reality, ambient light is as complex as the scene itself; however, in computer graphics, ambient light is often grossly simplified by treating it as a constant, which is like assuming that an object is situated in a uniformly gray room. The radiosity technique (Cohen & Greenberg, 1985) properly models the complexity of ambient light, but it is rarely used for visualization. One of the consequences of modeling ambient light as a constant is that no shape-from-shading information is available in areas of cast shadow. In Figures 2.6(b) and 2.6(c), ambient light is simulated by the assumption that a constant amount of light is reflected from all points on the surface. Ambient light is reflected both specularly and nonspecularly.
- ***Cast shadows.*** An object can cast shadows either on itself or on other objects. As shown in Figure 2.6(c), cast shadows can greatly influence the perceived height of an object.

The mathematical expression for the amount of light reflected, r, toward a particular viewpoint, according to this simplified model, is as follows:

$$r = \boldsymbol{a} + \boldsymbol{b} \cos(\theta) + \boldsymbol{c} \cos^k(\alpha) \tag{2.1}$$

where θ is the angle between the incident ray and the surface normal, α is the angle between the reflected ray and the view vector, and $\boldsymbol{a}$, $\boldsymbol{b}$, and $\boldsymbol{c}$ represent the relative amounts of ambient, Lambertian, and specular light, respectively. The exponent k is used to control the degree of glossiness. A high value of k, such as 50, models a very shiny surface, whereas a lower value, such as 6, results in a semigloss appearance. Note that this is a simplified treatment, providing only the crudest approximation of the way light interacts with surfaces, but nevertheless it is so effective in creating real-looking scenes that it is widely used in computer graphics with only a small modification to simulate color. It is sufficient for most visualization purposes. This surface/light interaction model and others are covered extensively by computer graphics texts concerned with realistic image synthesis. More information can be found in Shirley and Marschner (2009) or any other standard computer graphics text.

What is interesting is that these simplifying assumptions may, in effect, be embedded in our visual systems. The brain may assume a model similar to this when we estimate the shape of a surface defined by shading information. Arguably, using more sophisticated modeling of light in the environment might actually be detrimental to our understanding of the shapes of surfaces. Chapter 7 discusses the way we perceive this shape-from-shading information.

Figures 2.7 and 2.8 illustrate some consequences of the simplified lighting model. Figure 2.7 shows glossy leaves to make the point that the simplified model is representative of at least some nonsynthetic objects. In this picture, the specular highlights from the shiny surface are white because the illuminant is white. The nonspecular light from the leaf pigmentation is green. As a tool in data visualization, specular reflection

Figure 2.7 Note how the highlights are the color of the illuminant on glossy leaves.

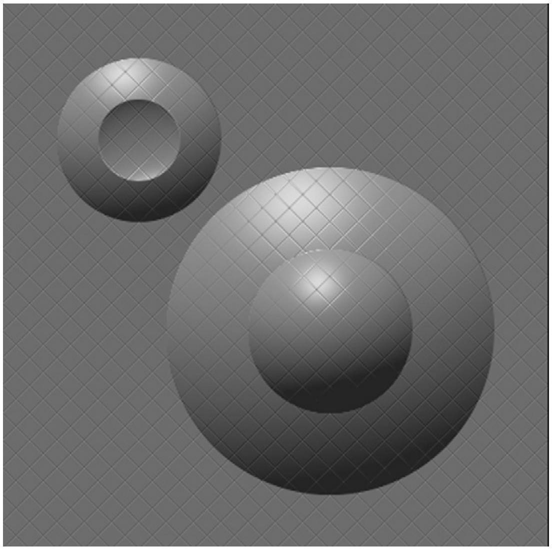


Figure 2.8 Specular light can reveal fine details of surface structure, depending on the viewpoint.

is useful in visualization of fine surface features, such as scratches on glass. The effect is illustrated in Figure 2.8, in which the grid lines are most distinct in the region of specular reflection. Specular highlights can be similarly useful in revealing subtle differences in surface micro-roughness. The nonspecular Lambertian reflection is more effective in giving an overall impression of the shape of the surface.

The different kinds of information contained in the different lighting models suggest the following three guidelines:

> **[G2.1]** Use Lambertian shading to reveal the shapes of smooth surfaces.

> **[G2.2]** Use specular shading to reveal fine surface details. Make it possible to move the light source or rotate the object so that specular light is reflected from regions of critical interest.

> **[G2.3]** Consider using cast shadows to reveal large-scale spatial relationships. Shadows should be created only where the connection between the shadow and the casting object is clear and where the value of the additional information outweighs the information that it obscured.

Another source of spatial information can come from the amount of ambient light that reaches into the interstices of an object. This is called *ambient occlusion* because in the depths of hollows some of the ambient light is occluded by other parts of the object. Tarini et al., (2006) used ambient occlusion to help reveal the shape of a complex molecule (Figure 2.9). The generality of this technique may be questioned, however, because the object on the left in Figure 2.9 is highly unusual in that it provides no Lambertian shading information, shading is only applied to individual spheres, not to the overall shape of the molecule.

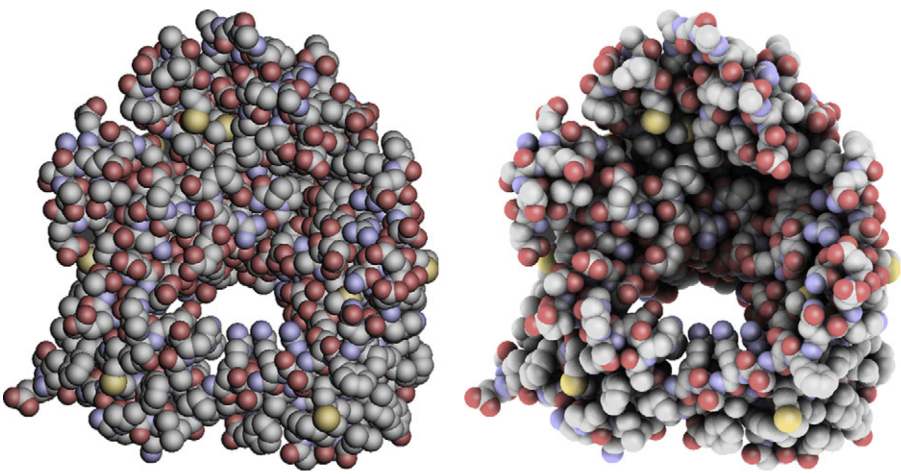


Figure 2.9 In the molecule on the left, only individual atoms are shaded. In the molecule on the right, the amount of ambient light reaching the inner parts of the molecule is reduced due to occlusion by the outer atoms.

[G2.4] Consider applying ambient occlusion in the lighting model to support two-dimensional (2D) shape perception for objects that otherwise supply no shading information.

To summarize this brief introduction to the visual environment, we have seen that much of what is useful to organisms is related to objects, to their layout in space, and to the properties of their surfaces. As Gibson so effectively argued, in understanding how surfaces are perceived, we must understand how light becomes structured when it arrives at the eye. We have covered two important kinds of structuring. One is the structure that is present in the ambient array of light that arrives at a viewpoint. This structure has both static pattern components and dynamic pattern flows as we move through the world. The second is the more detailed structuring of light that results from the interaction of light with surfaces. In data the goal is to use rendering techniques that best convey the important information, not to obtain photorealistic realism.

The Eye

We now consider the instrument of sight. The human eye, like a camera, contains a variable focus lens, an aperture (the pupil), and a sensor array (the retina). Figure 2.10 illustrates these parts. The lens focuses a small, inverted picture of the world onto

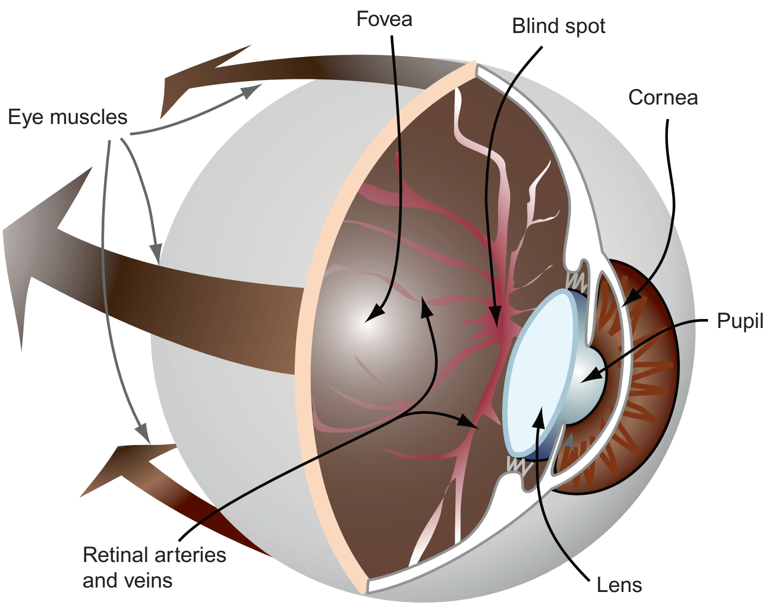


Figure 2.10 The human eye. Important features include the fovea, where vision is sharpest; the pupil, a round aperture through which light enters the eye; the two principal optical elements, the lens and the cornea; and the large eye muscles that control eye movements. This blind spot is caused by the absence of receptors where the retinal arteries enter the eyeball.

the retina. The iris performs the function of a variable aperture, helping the eye to adjust to different lighting conditions. Some people find it difficult to understand how we can see the world properly when the image is upside down. The right way to think about this is to adopt a computational perspective. We do not perceive what is on the retina; instead, a percept is formed through a complex chain of neural computations. A control computer does not care which way is up, and inversion of the image is the least of the brain's computational problems.

We should not take the eye/camera analogy too far. If seeing were like photography, you would only have to copy the image on the back of the eye to produce a perfect likeness of a friend; anyone could be a great portrait painter. Yet, artists spend years studying perspective geometry and anatomy and constantly practice their skills. It took thousands of years, culminating in the golden age of Greek art, for artists to develop the skills to draw natural figures, properly shaded and foreshortened. Following this, the skill was largely lost again until the Renaissance, in the 15th century. Yet, in the image on the back of the eye, everything is in perfect proportion and in perspective. Clearly, we do not "see" what is on the retina. The locus of conscious perception is farther up the chain of processing, and at this later stage most of the simple properties of the retinal image have been lost.

The Visual Angle Defined

The visual angle is a key concept in defining the properties of the eye and early vision. As Figure 2.11 illustrates, a visual angle is the angle subtended by an object at the eye of an observer. Visual angles are generally defined in degrees, minutes, and seconds of arc. (A minute is 1/60 degree and a second is 1/60 minute). As a useful approximation, a thumbnail held at arm's length subtends about 1 degree of visual angle. Another useful fact is that a 1-cm object viewed at 57 cm has a visual angle of approximately 1 degree, and 57 cm is a reasonable approximation for the distance at which we view a computer monitor. To calculate visual angle, use this equation:

$$\tan\left(\frac{\theta}{2}\right) = \frac{h}{2d} \tag{2.2}$$

$$\theta = 2\arctan\left(\frac{h}{2d}\right) \tag{2.3}$$

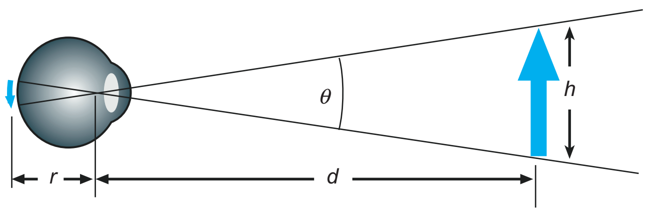


Figure 2.11 The visual angle of an object is measured from the optical center of the eye.

Lens

The human eye contains a compound lens. This lens has two key elements: the curved front surface of the cornea and the crystalline lens. The nodal point is the optical center of the compound lens; it is positioned approximately 17 mm from the retina. The distance from the eye to an object is usually measured from the cornea, but in terms of optics it is better to estimate the distance from the nodal point (see Figure 2.11). The following equation describes the imaging properties of a simple lens:

$$\frac{1}{f} = \frac{1}{d} + \frac{1}{r} \tag{2.4}$$

where f is the focal length of the lens, d is the distance to the object that is imaged, and r is the distance to the image that is formed. If the units are meters, the *power* of a lens is given by the reciprocal of the focal length ($1/f$) in units of *diopters*. Thus, a 1-diopter lens has a focal length of 1 m. The 17-mm focal length of the human lens system corresponds to a power of 59 diopters. To get this from Equation 2.3, consider viewing an object at infinity ($d = \infty$).

To a first approximation, the power of a compound lens can be computed by adding the powers of the components. We obtain the focal length of a two-part compound lens by using the following equation:

$$\frac{1}{f_3} = \frac{1}{f_1} + \frac{1}{f_2} \tag{2.5}$$

where f_3 is the result of combining lenses f_1 and f_2.

In the compound lens of the human eye, most of this power, about 40 diopters, comes from the front surface of the cornea; the remainder comes from the variable-focus lens. When the cillary muscle that surrounds the lens contracts, the lens assumes a more convex and more powerful shape, and nearby objects come into focus. Young children have very flexible lenses, capable of adjusting over a range of 12 diopters or more, which means that they can focus on an object as close as 8 cm. However, the eye becomes less flexible with age, at roughly the rate of 2 diopters per decade, so that by the age of 60 the lens is almost completely rigid (Sun et al., 1988), hence the need for reading glasses at about the age of 48, when only a few diopters of accommodation are left.

The *depth of focus* of a lens is the range over which objects are in focus when the eye is adjusted for a particular distance. The depth of focus of the human eye varies with the size of the pupil (Smith & Atchison, 1997), but assuming a 3-mm pupil and a human eye focused at infinity, objects between about 3 m and infinity are in focus. Depth of focus can usefully be described in terms of the power change that takes place without the image becoming significantly blurred. This is about 1/3 diopter for a 3-mm pupil.

Assuming the 1/3-diopter depth-of-focus value and an eye focused at distance d (in meters), objects in the range:

$$\left[\frac{3d}{d+3}, \frac{-3d}{d-3}\right] \tag{2.6}$$

Table 2.1 *Depth of Focus at Various Viewing Distances*

Viewing distance	Near	Far
50 cm	43 cm	60 cm
1 m	75 cm	1.5 m
2 m	1.2 m	6.0 m
3 m	1.5 m	Infinity

will be in focus. To illustrate, for an observer focusing at 50 cm, roughly the normal monitor viewing distance, an object can be about 7 cm in front of the screen or 10 cm behind the screen before it appears to be out of focus. In helmet-mounted displays, it is common to use lenses that set the screen at a virtual focal distance of 2 m. This means that in the range 1.2 m to 6.0 m it is not necessary to worry about simulating depth-of-focus effects, something that is difficult and computationally expensive to do. In any case, the large pixels in typical virtual-reality displays prevent us from modeling image blur to anywhere near this resolution.

Table 2.1 gives the range that is in focus for a number of viewing distances, given a 3-mm pupil. For more detailed modeling of depth of focus as it varies with pupil diameter, consult Smith and Atchison (1997).

Optics and Augmented-Reality Systems

Augmented-reality systems involve superimposing visual imagery on the real world so that people can see a computer-graphics-enhanced view of the world. For this blending of real and virtual imagery to be achieved, the viewpoint of the observer must be accurately known and the objects' positions and shapes in the local environment must also be stored in the controlling computer. With this information, it is a straightforward application of standard computer graphics techniques to draw 3D images that are superimposed on the real-world images. Getting the perspective right is easy; the difficult problems to solve include accurately measuring the observer's eye position, which is essential to precise registration, and designing optical systems that are light, undistorted, and portable.

Figure 2.12 illustrates an experimental augmented-reality system in which a surgeon sees a brain tumor highlighted within the brain during surgical planning or to guide a biopsy needle (Grimson et al., 1996). Given how difficult it is for the surgeon to accomplish this task, such a development would have very large benefits. Other applications for augmented displays include aircraft maintenance, where the mechanic sees instructions and structural diagrams superimposed on the actual machinery; tactical military displays, in which the pilot or tank driver sees indicators of friendly or hostile targets superimposed on a view of the landscape; and shopping, where information about a potential purchase appears next to the item. In each case, visual data is

Figure 2.12 Augmented reality has been used experimentally in the medical field. Here, an image of a tumor is superimposed on a patient's head. (*From Grimson et al. (1996). Reproduced with permission*.)

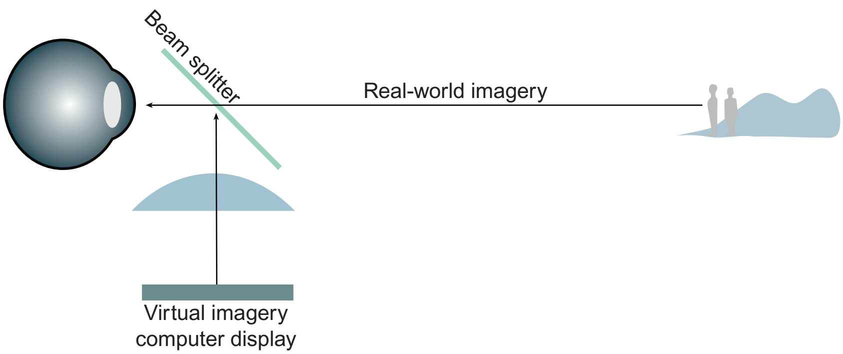


Figure 2.13 In augmented-reality displays, computer graphics imagery is superimposed on the real-world environment using a beam splitter. The effect is like a transparent overlay on the environment. The focal distance of the computer imagery depends on the power of the lenses used.

superimposed on real objects to supplement the information available to the user and enable better or more rapid decision making. This data may take the form of written text labels or sophisticated symbology.

In many augmented-reality systems, a device called a beam splitter is used to superimpose computer graphics imagery on the environment. The splitter is actually used not to split but to combine the images coming from the real world with those presented on a small computer monitor. The result is like a double-exposed photograph. A typical beam splitter allows approximately half the light to pass through and half the light to be reflected. Figure 2.13 illustrates the essential optical components of this type of display.

Because the optics are typically fixed, in augmented-reality systems there is only one depth at which both the computer-generated imagery and the real-world imagery are in focus. This can be both good and bad. If real-world and virtual-world scenes are both in focus, it will be easier to perceive them simultaneously. If this is desirable, care should be taken to set the focal plane of the virtual imagery at the typical depth of the real imagery. It is sometimes desirable, however, that the computer imagery remain perceptually distinct from the real-world image; for example, a transparent layer of text from an instruction manual might be presented on a see-through display (Feiner et al., 1993). If the focal distances are different, the user can choose to focus either on the text or on the imagery and in this way selectively attend to one or the other.

[G2.5] In augmented-reality systems, an augmenting image linked to an external object should be at the same focal distance.

[G2.6] In augumented-reality systems, when augmenting imagery does not need to be linked to external objects, the focal distance of the augumenting imagery should be closer, which will reduce visual interference. This will not work for older users who have little or no ability to change the focus of their eyes.

There is evidence that focus can cause problems with distance estimation in aircraft heads-up displays (HUDs). In these displays, the virtual image is set at optical infinity, because only distant objects are normally seen through a cockpit screen. Despite this, experiments have shown that observers tend to focus at a distance closer than infinity with HUDs, and this can cause overestimation of distances to objects in the environment (Roscoe, 1991). This may be a serious problem; according to Roscoe, it has been at least partially responsible for large numbers (one per month) of generally fatal "controlled flight into the terrain" accidents in the U.S. Air Force.

Roscoe's theory of what occurs is that in normal vision the average apparent size of objects is almost perfectly correlated with the distance at which the eyes are focused (Iavecchia et al., 1988). But, with HUDs, the eyes are focused closer (for reasons that are not fully understood), leading to an underestimation of size and an overestimation of distance. Roscoe suggests that this can also partially account for the fact that when virtual imaging is used, either in simulators or in real aircraft with HUDs, pilots make fast approaches and land hard.

There are a number of other optical and perceptual problems with head-mounted displays (HMDs). The complex optics of progressive eyeglass lenses is not compatible with HMD optics. With progressive glasses, the optical power varies from top to bottom of the lens. Also, people normally use coordinated movements of both the eyes *and the head* to conduct visual searches of the environment, and HMDs do not allow for redirection of the gaze with head movements. Ordinarily, when the angular movement of the eyes to the side is large, head movements actually begin first. Peli (1999) suggests that looking sideways more than 10 degrees off the center line is very uncomfortable to maintain. With an HMD the image moves with the head, so compensatory head movements will fail to eliminate the discomfort.

> **[G2.7]** When using a head-mounted display to read text, make the width of the text area no more that 18 degrees of visual angle.

Another problem is that see-through HMDs are typically only worn over one eye, and the effect of binocular rivalry means that parts of the visual world and HMD imagery are likely to spontaneously appear and disappear (Laramee & Ware, 2002). Someone wearing such a display while walking along a sidewalk would be likely to walk into lampposts!

Optics in Virtual-Reality Displays

Virtual-reality (VR) displays block out the real world, unlike the see-through augmented-reality displays discussed previously. The VR system designer need only be concerned with computer-generated imagery. It is still highly desirable, however, that correct depth-of-focus information be presented to the user. Ideally, objects on which the user fixates should be in sharp focus, while objects farther away or nearer should be blurred to the appropriate extents. Focus is important in helping us to differentiate objects that we wish to attend to from other objects in the environment.

Unfortunately, simulating depth of focus using a flat-screen display is difficult. The problem has two parts: simulating optical blur and simulating the optical distance of the virtual object. There is also the problem of knowing what the user is looking at so that the object of attention can be made sharp while other objects are displayed as though out of focus. Figure 2.14 illustrates one way that correct depth-of-focus information could be presented on a flat-screen VR display. An eye tracker is used to determine where in the scene the eye is fixated. If binocular eye trackers were used in a stereoscopic display, they would have to be accurate enough for convergence information to be used to estimate the distance to a fixated object.

Once the object of attention is identified by the computer, it constructs an image in such a way that the fixated object is in sharp focus and other objects are appropriately out of focus. A sophisticated system might measure pupil diameter and take this information into account. At the same time, other system components change the focal lengths of the lenses in the display system so that the attended virtual object is placed at the correct focal distance (Liu & Hua, 2009). All virtual objects are actually displayed on the screen in the conventional way, but with simulated depth of focus based on the properties of the human eye. Neveau and Stark (1998) described the optical and control requirements of such a system.

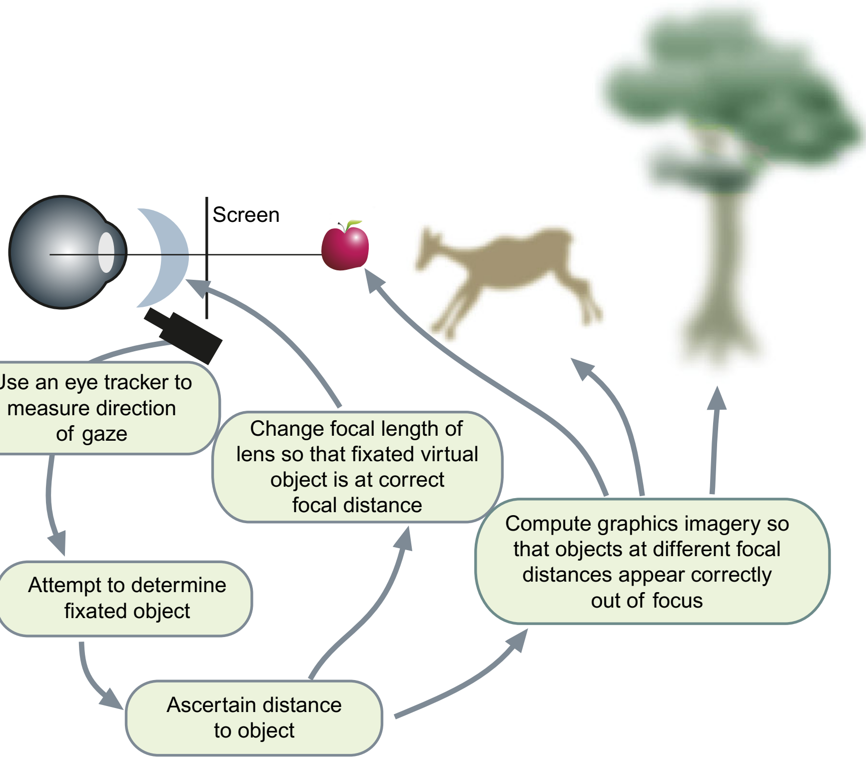


Figure 2.14 A possible solution to the problem of how correct depth-of-focus information might be displayed in a virtual-reality (VR) display. The apple is the fixated object and is drawn in sharp focus. The other objects are drawn out of focus, depending on their relative depths.

Chromatic Aberration

The human eye is not corrected for chromatic aberration. Chromatic aberration means that different wavelengths of light are focused at different distances within the eye. Short-wavelength blue light is refracted more than long-wavelength red light. A typical monitor has a blue phosphor peak wavelength at about 480 nm and a red peak at about 640 nm, and a lens with a power of 1.5 diopters is needed to make blue and red focus at the same depth. This is the kind of blur that causes people to reach for their reading glasses. If we focus on a patch of light produced by the red phosphor, an adjacent blue patch will be significantly out of focus. Because of chromatic aberration, it is inadvisable to make fine patterns that use undiluted blue phosphor on a black background. Pure blue text on a black background can be almost unreadable, especially if there is white or red text nearby to attract the focusing mechanism. The addition

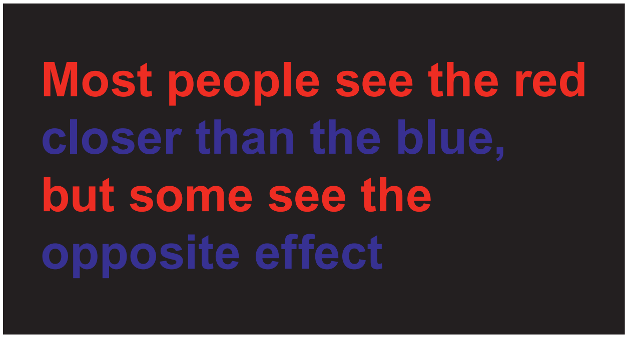


Figure 2.15 Chromostereopsis. For most people, red seems nearer than blue on a black background.

of even a small amount of red and green will alleviate the problem, because these colors will provide luminance edges to perceptually define the color boundary.

The chromatic aberration of the eye can give rise to strong illusory depth effects (Jackson et al., 1994), although the actual mechanism remains unknown. This is illustrated in Figure 2.15, where both blue text and red text are superimposed on a black background. For about 60% of observers, the red appears closer, but 30% see the reverse, and the remaining 10% see the colors lying in the same plane. It is common to take advantage of this in slide presentations by making the background a deep blue, which makes white or red lettering appear to stand out for most people.

Receptors

The lens focuses an image on a mosaic of photoreceptor cells that line the back of the eye in a layer called the *retina*. There are two types of such cells: rods, which are extremely sensitive at low light levels, and cones, which are sensitive under normal working light levels. There are about 100 million rods and only 6 million cones. Rods contribute far less to normal daytime vision than cones do. The input from rods is pooled over large areas, with thousands of rods contributing to the signal that passes up through a single fiber in the optic nerve. Rods are so sensitive that they are overloaded in daylight and effectively shut down; therefore, most vision researchers ignore their very slight contribution to normal daylight vision.

The fovea is a small area in the center of the retina that is densely packed only with cones, and it is here that vision is sharpest. Cones at the fovea are packed about 20 to 30 seconds of arc apart (180 per degree). There are more than 100,000 cones packed into this central small area, subtending a visual angle of 1.5 to 2 degrees. Although it is usual to speak of the fovea as a 2-degree field, the greatest resolution of detail is obtained only in the central 1/2 degree of this region. Remember that 1 degree is about the size of your thumbnail held

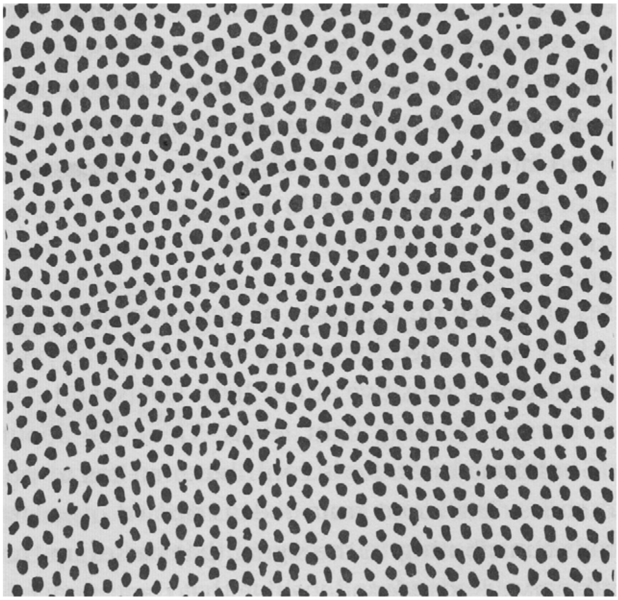


Figure 2.16 The receptor mosaic in the fovea.

at arm's length. Figure 2.16 is an image of the receptor mosaic in the fovea. The receptors are arranged in an irregular but roughly hexagonal pattern.

Simple Acuities

Visual acuities are measurements of our ability to see detail. Acuities are important in display technologies because they give us an idea of the ultimate limits on the information densities that we can perceive. Some of the basic acuities are summarized in Figure 2.17.

Most of the acuity measurements in Figure 2.17 suggest that we can resolve things, such as the presence of two distinct lines, down to about 1 minute of arc. This is in rough agreement with the spacing of receptors in the center of the fovea. For us to see that two lines are distinct, the blank space between them should lie on a receptor; therefore, we should only be able to perceive lines separated by roughly twice the receptor spacing. However, there are a number of superacuities; vernier acuity and stereo acuity are two examples. A superacuity is the ability to perceive visual properties of the world to a greater precision than could be achieved based on a simple receptor model. Superacuities can be achieved only because postreceptor mechanisms are capable of integrating the input from many receptors to obtain better than single-receptor resolution. A good example of this is vernier acuity, the ability to judge the colinearity of two fine line segments. This can be done with amazing accuracy to better than 10 seconds of arc. To give an idea of just how accurate this is, a normal computer monitor has about 40 pixels (picture elements) per centimeter. We can perform vernier acuity tasks that are accurate to about 1/10 of a pixel.

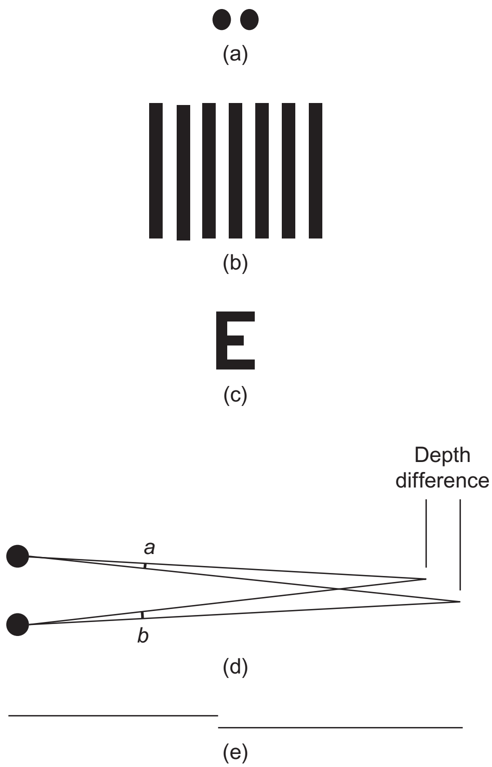


Figure 2.17 The basic acuities. (a) Point acuity (1 minute of arc): The ability to resolve two distinct point targets. (b) Grating acuity (1 to 2 minutes of arc): The ability to distinguish a pattern of bright and dark bars from a uniform gray patch. (c) Letter acuity (5 minutes of arc): The ability to resolve letters. The Snellen eye chart is a standard way of measuring this ability. 20/20 vision means that a 5-minute letter can be seen 90% of the time. (d) Stereo acuity (10 seconds of arc): The ability to resolve depth. The acuity is measured as the difference between two angles (*a* and *b*). (e) Vernier acuity (10 seconds of arc): The ability to see if two line segments are collinear.

Neural postprocessing can efficiently combine input from two eyes. Campbell and Green (1965) found that binocular viewing improves acuity by 7% as compared with monocular viewing. They also found a $\sqrt{2}$ improvement in contrast sensitivity. This latter finding is remarkable because it supports the theory that the brain is able to perfectly pool information from the two eyes, despite the three or four synaptic connections that lie between the receptors and the first point at which the information from the two eyes can be combined. Interestingly, Campbell and Green's findings suggest that we should be able to use the ability of the eye to integrate information over space and time to allow perception of higher resolution information than is actually available on our display device. One technique for achieving higher than device resolution is antialiasing, which is discussed later in this chapter. There is also an intriguing possibility that the temporal integration capability of the human eye could be used to advantage. This is why a sequence of video frames seems of substantially higher quality than any single frame.

Acuity Distribution and the Visual Field

If we look directly ahead and hold our arms straight out to either side, then we can just see both hands when we wiggle our fingers. This tells us that both eyes together provide a visual field of a bit more than 180 degrees. The fact that we cannot see our fingers until they move also tells us that motion sensitivity in the periphery is better than static sensitivity. Figure 2.18 illustrates the visual field and shows the roughly triangular region of binocular overlap within which both eyes receive input. The reason that there is not more overlap is that the nose blocks the view. Visual acuity is distributed over this field in a very nonuniform manner. As shown in Figure 2.19, acuity outside of the fovea drops rapidly, so that we can only resolve about one-tenth the detail at 10 degrees from the fovea.

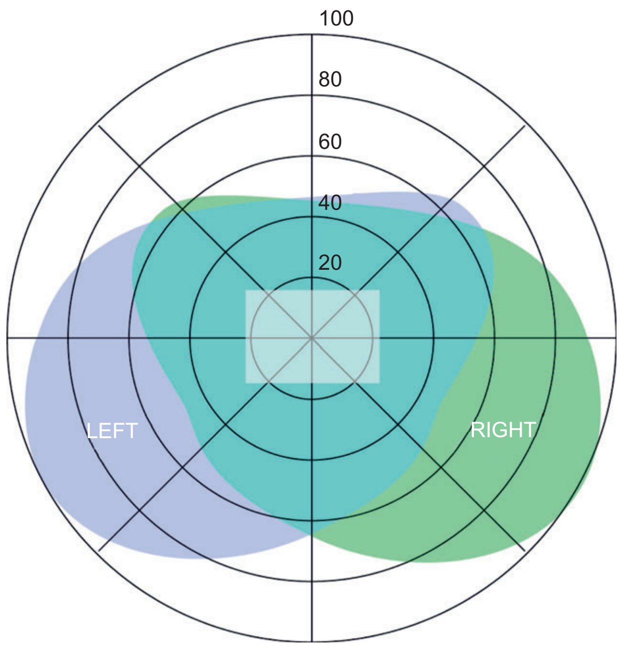


Figure 2.18 The visual field of view for a person gazing straight ahead. The irregular boundaries of the left and right fields are caused by facial features such as the nose and eyebrow ridges. The central blue–green area shows the region of binocular overlap. The rectangle at the center is the area covered by a monitor at a typical viewing distance.

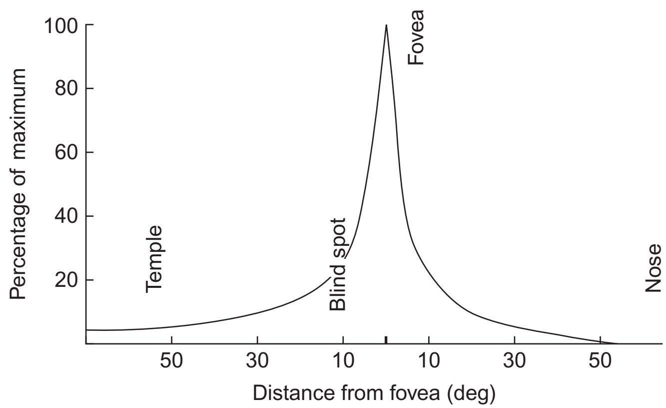


Figure 2.19 The acuity of the eye falls off rapidly with distance from the fovea.

Normal acuity measures are one dimensional; they measure our ability to resolve two points or two parallel lines as a function of the distance between them. But, if we consider the total number of points that can be perceived per unit area, this measure falls according to an inverse square law. We can actually only see one hundredth the number of points in an area at 10 degrees of eccentricity from the fovea. To put it another way, in the middle of the visual field, at the fovea, we can resolve about 100 points on the head of a pin. At the edge of the visual field, we can only discriminate objects the size of a fist.

The variation in acuity has been vividly expressed in an eye chart developed by Stuart Anstis (1974). The chart is shown in Figure 2.20. If you look at the center of the chart, each of the characters is equally distinct. To make this chart, Anstis took measurements of the smallest letter that could be seen at many angles of eccentricity from the fovea. In this version, each letter is about 5 times the smallest resolvable size for people with 20/20 vision. Anstis found that the size of the smallest distinct characters could be approximated by the simple function:

$$\textit{Character Size} = 0.046e \tag{2.7}$$

where e is the eccentricity from the fovea measured in degrees of visual angle.

This variation in acuity with eccentricity comes from something called *cortical magnification*. Visual area 1 (V1) is the primary cortical reception area for signals from the eye. Fully half of the neurons in V1 are devoted to processing signals from the central 10 degrees of vision, representing only about 3% of the visual field.

Because space in the brain is carved up very differently than the uniform pixels of a computer screen, we need a new term to talk about the image units used by the brain to process space. Let's call them *brain pixels*. Although there are many areas in the brain with nonuniform image maps, retinal ganglion cells best capture the brain pixel idea. Retinal ganglion cells are neurons that send information from the eyeball up the optic nerve to the cortex. Each one pools information from many rod and cone receptors, as illustrated in Figure 2.21. In the fovea, a single ganglion cell may be devoted to

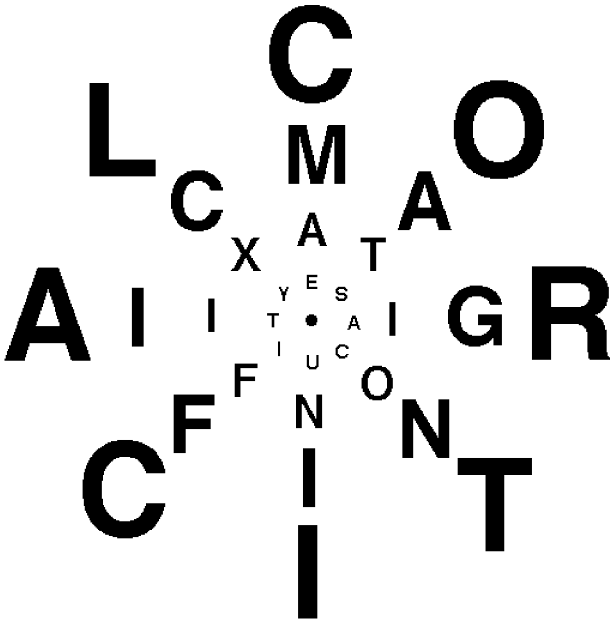


Figure 2.20 An eye chart developed by Anstis (1974). Each character is about five times the smallest perceivable size when the center is fixated. This is the case for any viewing distance.

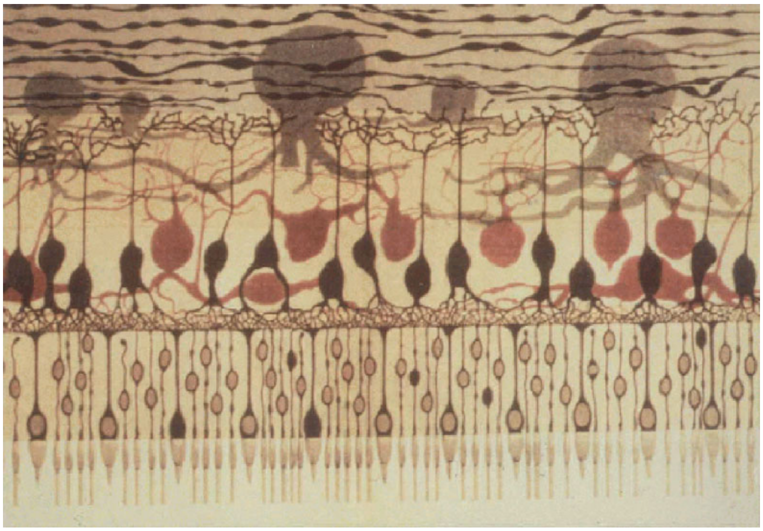


Figure 2.21 The retina is comprised of receptors and several layers of neurons. The big octopus-like neurons at the top of this drawing are retinal ganglion cells. Each integrates information from many receptors and transmits it to the brain. (*Illustration by Ferruccio Tartufieri (1887)*.)

a single cone, whereas in the far periphery each ganglion cell receives information from thousands of rods and cones. Each neuron has one nerve fiber called an *axon*, which carries the signal from each ganglion cell, and there are about a million axons in each optic nerve. The visual area that feeds into a ganglion cell is called its *receptive field*. Drasdo (1977) found that retinal ganglion cell size could be approximated by the function:

$$\textit{Receptive Field Size} = 0.006(e + 1.0) \tag{2.8}$$

where e is the eccentricity from the fovea measured in degrees of visual angle. Note that Equation 2.8 is very similar to Anstis' equation (2.7) when we take into account that many brain pixels are needed to resolve something as complex as a letter of the alphabet. Assuming that a 7 × 7 matrix of brain pixels is needed to represent a character brings the two functions into close agreement.

Brain Pixels and the Optimal Screen

In light of the extreme variation in the sizes of brain pixels, we can talk about the visual efficiency of a display screen by asking what screen size provides the best match of screen pixels to brain pixels. What happens when we look at the very wide-angle screen provided by some head-mounted virtual-reality displays? Are we getting more information into the brain, or less? What happens when we look at the small screen of a personal digital assistant or even a wristwatch-sized screen? One way to answer these questions is to model how many brain pixels are stimulated by different screens having different sizes but the same number of pixels. To make the comparison fair, we should keep the viewing distance constant. The two types of inefficiency that occur when we view flat displays are illustrated in Figure 2.22. At the fovea, there are many brain pixels for each screen pixel. To have higher-resolution screens would definitely help foveal vision; however, off to the side, the situation is reversed, as there are many more screen pixels than brain pixels. We are, in a sense, wasting information, because the brain cannot appreciate the detail and we could easily get away with fewer pixels. In modeling the visual efficiency of different screen sizes, we can compute the *total number of brain pixels (TBP)* stimulated by the display simply by adding up all of the retinal ganglion cells stimulated by a display image.

We can also compute the number of *uniquely stimulated brain pixels (USBP).* Many brain pixels get the same signal when we look at a low-resolution screen and are therefore redundant, providing no extra information. Therefore, to count uniquely stimulated brain pixels, we use the following formula:

$$USBP = TBP - \textit{redundant brain pixels} \tag{2.9}$$

To obtain a measure of how efficiently a display is being used, we take the ratio of USBP to *screen pixels (SP)*. This measure is called *display efficiency (DE).*

$$DE = USBP/SP \tag{2.10}$$

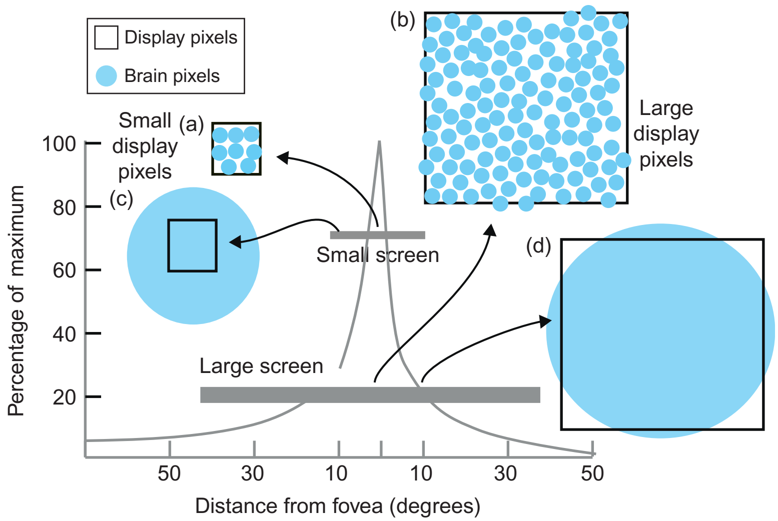


Figure 2.22 Differently sized screens having the same number of pixels have different areas of visual inefficiency. (a) With the small screen, there are 10 brain pixels per screen pixel at the center of the fovea. (b) With the large screen, the situation is worse, as there are 100 brain pixels per screen pixel at the center of the fovea. (c) At the edge of the small screen display, pixels are smaller than brain pixels. (d) At 10 degrees of eccentricity, with the big screen there is an approximate match between screen pixels and brain pixels.

Note that if there were a perfect match, with one screen pixel for every brain pixel, we would have a display efficiency of 1.0, or 100%, but this is never the case because screen pixels are uniformly distributed and brain pixels are not.

Finally, we might be interested in the ratio between USBP and the brain pixels covered by a display. This measure of *visual efficiency (VE)* tells us the proportion of brain pixels in the screen area that are getting unique information.

$$VE = USBP/TBP \tag{2.11}$$

Figure 2.23 illustrates a numerical simulation of what happens to TBP and USBP as we change the size of the screen. It is based on Drasdo's (1977) model and assumes 1 million square pixels in a 1000 × 1000 array at a constant viewing distance of 50 cm. It takes into account that pixels near the edge of a large screen are both farther away and viewed obliquely—and are therefore visually smaller than pixels in the center. In fact, their visual area declines by $\cos^2(\theta)$, where θ is the angle of eccentricity. For illustrative purposes, the display widths equivalent to a conventional monitor and a single wall of a Cave Automatic Virtual Environment (CAVE) display are shown (Cruz-Neira et al., 1992). A CAVE is a virtual-reality display where the participant stands in the center of a cube, each wall of which is a display screen. In Figure 2.23, the sizes have been normalized to a standard viewing distance by using equivalent

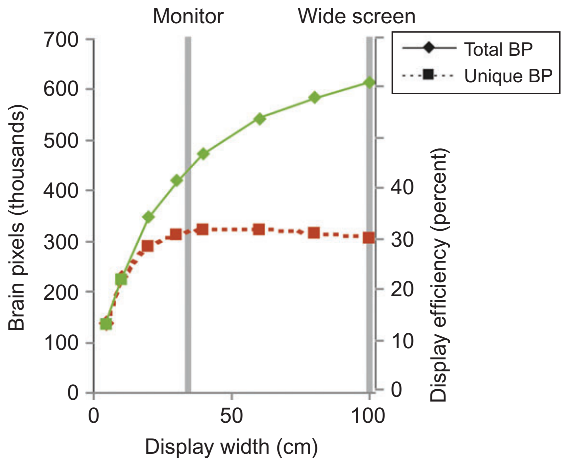


Figure 2.23 Results from a numerical simulation with a 1-million-pixel screen to show how many brain pixels are stimulated as a display increases in size. Display efficiency (right-hand scale) gives the percentage of screen pixels that uniquely influence the visual system (unique brain pixels) and only applies to the lower curve.

visual angles. Thus, a CAVE wall of 2 meters at a viewing distance of 1 meter is equivalent to a 1 meter display at 50 centimeters, given that both have the same number of pixels.

The simulation of the one-million pixel display reveals a number of interesting things. For a start, even though a conventional monitor covers only about 5 to 10% of our visual field when viewed normally, it stimulates almost 50% of our brain pixels. This means that even if we could have very high-resolution large screens, we would not be getting very much more information into the brain. Figure 2.23 shows that USBPs peak at a width close to the normal monitor viewing with a display efficiency of 30%, and decline somewhat as the screen gets larger. If we consider that our visual field is a precious resource and there are other things besides computer graphics that we may wish to see, this confirms that computer screens are currently about the right size for most tasks.

There is an argument that the center of the visual field is even more important for many tasks than its huge brain pixel concentration would suggest. A natural way of seeking information (discussed in Chapter 11) is to use eye movements to bring the information to the center of the visual field where we see the best. The *parafovea* may be optimal for pattern perception; it is an area that is about 6 degrees in diameter, centered on the fovea. Most charts and diagrams in this book are presented to be roughly parafoveal size. The periphery is undoubtedly important in situation awareness and alerting, but when visual pattern finding for decision making is required, the relatively small parafoveal region is the most critical.

The StarCAVE (DeFanti et al., 2009) is, at the time of this writing, perhaps the highest resolution completely immersive display currently available. It is a five-sided room with curved walls on which a total of 68 million pixels are projected, 34 million for each eye. Compare this with a high-quality monitor having about 2 million pixels or a high-quality cell phone display at about one-third of a million pixels.

The StarCAVE and its four-walled CAVE predecessors are the only displays that can fill the visual field of the eye. This arguably makes it very good for simulating the feel of an architectural space or for other simulator applications where a sense of presence is important. *Presence* is a term used by those who strive for virtual realism and is used to describe the degree to which virtual objects and spaces seem real.

But presence is not usually important in data visualization, and when we wish to understand the structure of a cell or the shape of a molecule, being inside of it does not help. We need to stand back. To best see the structure of a cell it should fill the parafovea, not the entire visual field, and ideally the most important information will fall on the fovea.

Of course, one conclusion to be drawn from this analysis is that we need more pixels in our displays. A display developed by IBM (T221) is only slightly larger than a normal desktop monitor, but it has 3840×2600 pixels, providing a visual quality close to that of high-quality printing. This means that when we move our eyes to a new spot we actually gain more information. The new iPhone displays make the most of a small screen by having a pixel density that matches the center of the fovea.

The brain's way of getting new information is to make rapid eye movements of about 5 degrees on average. In a StarCAVE, when we make a rapid eye movement we get only another 10% of our brain pixels stimulated in our parafoveal region because of the low resolution. With the IBM T221, at normal viewing distances, an eye movement generates at least an additional 60% of new information within the parafovea. Ultimately, what matters is the time and mental effort required to get new information. The final chapters of this book deal with this in detail. But, for now, it is worth saying that interactive methods combined with moderately sized high-resolution screens are likely to be much more efficient than low-resolution immersive screens. They also use much less of the working environment of the user and are not as costly.

[G2.8] Use a high-resolution display with a moderate viewing angle (e.g., 40 degrees) for data analysis. This applies both to individual data analysis when the screen can be on a desktop and close to the user and to collaborative data analysis when the screen must be larger and farther away.

[G2.9] Use wrap-around screens to obtain a sensation of "presence" in a virtual space. This is useful in vehicle simulations and some entertainment systems.

Spatial Contrast Sensitivity Function

The rather simple pattern shown in Figure 2.24 has become one of the most useful tools in measuring basic properties of the human visual system. This pattern is called a *sine wave grating* because its brightness varies sinusoidally in one direction. There are five ways in which this pattern can be varied:

1. Spatial frequency (the number of bars of the grating per degree of visual angle)
2. Orientation
3. Contrast (the amplitude of the sine wave)
4. Phase angle (the lateral displacement of the pattern)
5. Visual area covered by the grating pattern

The grating luminance is defined by the following equation:

$$L = 0.5 + \frac{a}{2}\sin\left(\frac{2\pi x}{\omega} + \frac{\phi}{\omega}\right) \tag{2.12}$$

where a is the contrast (amplitude), ω is the wavelength, ϕ is the phase angle, and x is the position on the screen. L denotes the resulting output light level in the range [0, 1], assuming that the monitor is linear (see the discussion of gamma correction in Chapter 3).

One way to use a sine wave grating is to measure the sensitivity of the eye/brain system to the lowest contrast that can be detected and to see how this varies with spatial frequency. Contrast is defined by:

$$C = \frac{L_{max} - L_{min}}{L_{max} + L_{min}} \tag{2.14}$$

where L_{max} is the peak luminance, L_{min} is the minimum luminance, and C is the contrast. The result is called a *spatial modulation sensitivity function.*

Figure 2.25 is a pattern designed to allow you to directly see the high-frequency falloff in the sensitivity of your own visual system. It is a sinusoidally modulated pattern of stripes that varies from left to right in terms of spatial frequency and from top to

Figure 2.24 A sine wave grating.

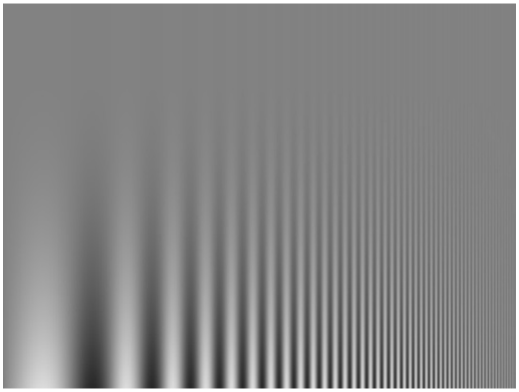


Figure 2.25 This grating pattern changes spatial frequency from the left to the right and varies in contrast in a vertical direction. The highest spatial frequency you can resolve depends on the distance from which you view the pattern.

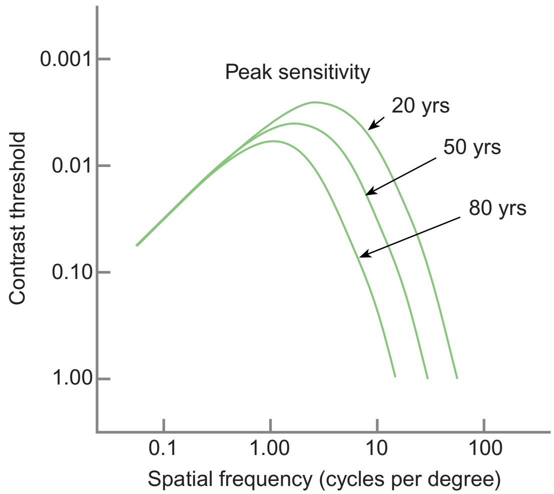


Figure 2.26 Contrast sensitivity varies with spatial frequency. The function is illustrated for three age groups. As we age, our sensitivity to higher spatial frequencies is reduced. (*Redrawn from Owlsley et al. (1983)*.)

bottom in terms of contrast. If you view this from 2 m, you can see how your sensitivity to high-frequency patterns is reduced. When it is close, you can also see a low-frequency falloff.

The human spatial contrast sensitivity function varies dramatically with spatial frequency, falling off at both high and low values. We are most sensitive to patterns of bright and dark bars occurring at about 2 or 3 cycles per degree. Figure 2.26 shows typical functions for three different age groups. Sensitivity falls off to zero for fine gratings of about 60 cycles per degree for younger people. As we age, we become less and less sensitive to higher spatial frequencies (Owlsley et al., 1983). It is not just that the finest detail we can resolve declines with age. We actually become less sensitive to any pattern components above 1 cycle per degree.

One of the practical implications of the low-frequency falloff in sensitivity is that many projectors are very nonuniform, yet this goes unremarked. A typical projector display will vary by 30% or more over the screen (it is usually brightest in the center), even if it is displaying a supposedly uniform field; but because we are insensitive to this very gradual (low-frequency) variation, we fail to notice the poor quality. Low spatial frequency acuity may also be critical for our perception of large spatial patterns as they are presented in large field displays.

Most tests of visual acuity, such as letter or point acuity, are really tests of high-frequency resolution, but this may not always be the most useful thing to measure. In tests of pilots, it has been shown that low-frequency contrast sensitivity is actually more important than simple acuity in measuring their performance in flight simulators (Ginsburg et al., 1982).

Visual images on the retina vary in time as well as in space. We can measure the temporal sensitivity of the visual system in much the same way that we measure the spatial sensitivity. This involves taking a pattern, such as that shown in Figure 2.24, and causing it to oscillate in contrast from high to low and back again over time. This temporal oscillation in contrast is normally done using a sinusoidal function. When this technique is used, both the spatial and the temporal sensitivity of human vision can be mapped out. Once this is done, it becomes evident that spatial frequency sensitivity and temporal frequency sensitivity are interdependent.

Figure 2.27 shows the contrast threshold for a flickering grating as a function of its temporal frequency and its spatial frequency (Kelly, 1979). This shows that optimal sensitivity is obtained for a grating flickering at between 2 and 10 cycles per second (Hz). It is interesting to note that the low-frequency falloff in sensitivity is much less when a pattern is flickering at between 5 and 10 Hz. If we were only interested in being able to detect the presence of blurry patterns in data, making those components of the image flicker at 7 or 8 Hz would be the best way to present them. There are many other reasons, however, why this is not a good idea; in particular, it would undoubtedly be extremely irritating. The limit of human sensitivity to flicker is about 50 Hz, which is why computer monitors and lightbulbs flicker at higher rates.

When the spatial and temporal frequency analysis of the visual system is extended to color, we find that chromatic spatial sensitivity is much lower, especially for rapidly changing patterns. In Chapter 4, the spatial and temporal characteristics of color vision are compared to those of the black-and-white vision we have been discussing.

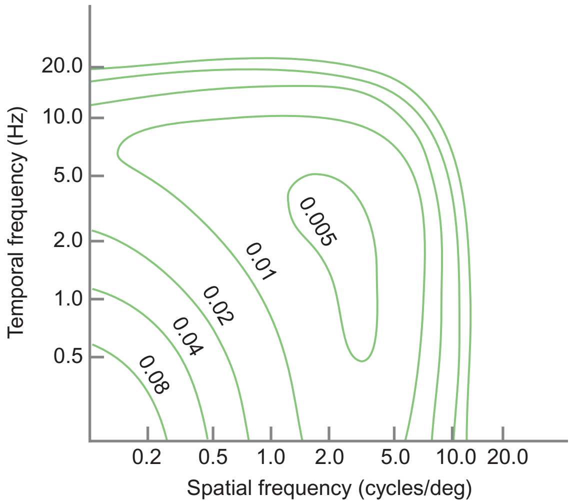


Figure 2.27 Contour map of the human spatiotemporal threshold surface. Each contour represents the contrast at which a particular combination of spatial and temporal frequencies can be detected. (*Redrawn from Kelly (1979)*.)

Visual Stress

On December 17, 1997, a Japanese television network canceled broadcasts of an action-packed cartoon because its brightly flashing scenes caused convulsions, and even vomiting of blood, in more than 700 children. The primary cause was determined to be the repetitive flashing lights produced by the computer-generated graphics. The harmful effects were exacerbated by the tendency of children to sit very close to the screen. Vivid, repetitive, large field flashes are known to be extremely stressful to some people.

The disorder known as *pattern-induced epilepsy* has been reported and investigated for decades. Some of the earliest reported cases were caused by the flicker from helicopter rotor blades; this resulted in prescreening of pilots for the disorder. In an extensive study of the phenomenon, Wilkins (1995) concluded that a particular combination of spatial and temporal frequencies is especially potent: Striped patterns of about 3 cycles per degree and flicker rates of about 20 Hz are most likely to induce seizures in susceptible individuals. Figure 2.28 illustrates a static pattern likely to cause visual stress. The ill effects also increase with the overall size of the pattern. Visual stress, however, may not be confined to individuals with a particular disorder. Wilkins argued that striped patterns can cause visual stress in most people. He gave normal text as an example of a pattern that may cause problems because it is laid out in horizontal stripes and suggested that certain fonts may be worse than others.

[G2.10] Avoid using high-contrast grating patterns in visual displays. In particular, avoid using high-contrast grating patterns that flicker or any pattern flickering at rates between 5 Hz and 50 Hz.

Warning! This pattern can cause seizures in some individuals.
If it causes you to feel ill effects, avoid looking at it.

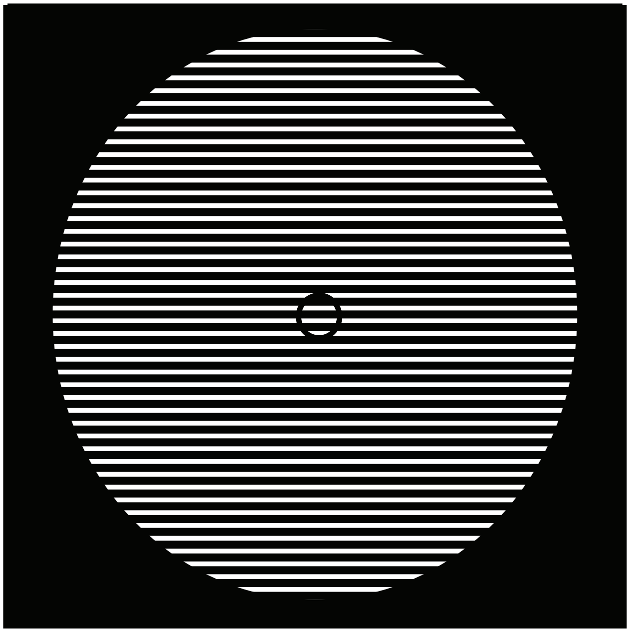


Figure 2.28 A pattern that is designed to be visually stressful. If it is viewed from 40 cm, the spacing of the stripes is about 3 cycles per degree.

The Optimal Display

Acuity information is useful in determining what is needed to produce either an adequate or an optimal visual display. A modern high-resolution monitor has about 35 pixels per centimeter. This translates to 40 cycles per degree at normal viewing distances. Given that the human eye has receptors packed into the fovea at roughly 180 per degree of visual angle, we can claim that in linear resolution we are about a factor of four from having monitors that match the resolving power of the human retina in each direction. A 4000×4000 pixel resolution monitor should be adequate for any conceivable visual task, leaving aside, for the moment, the problem of superacuities. Such a monitor would require 16 million pixels. The highest resolution monitor currently available is an IBM LCD display with 3840×2400 pixels, or more than 9 million pixels.

We come to a similar conclusion about the ultimate display from the spatial modulation transfer function. Humans can resolve a grating of approximately 50 cycles per degree in spatial frequency. If we take into account the sampling theory that states that we must sample at more than twice the highest frequency we wish to detect, this suggests that we need more than 100 pixels per degree. Perhaps 150 pixels per degree would be reasonable.

If 150 pixels per degree is sufficient, we must ask why manufacturers produce laser printers capable of 1200 dots per inch (460 dots per centimeter) or more. There are three reasons: aliasing, gray levels, and superacuities. The first two reasons are essentially technical, not perceptual, but they are worth discussing because they have significant implications in perception. The problems are significant for most display devices, not just for printers.

Aliasing

A fundamental theorem of signal transmission tells us that a signal can be reconstructed from its samples only if the samples are obtained at a frequency at least twice the highest frequency contained in the source. This is called the *Nyquist limit* (Gonzalez & Woods, 1993). Aliasing effects occur when a regular pattern is sampled by another regular pattern at a different spatial frequency. Figure 2.29 illustrates what happens when a pattern of black and white stripes is sampled by an array of pixels whose spacing is slightly greater than the wavelength. We assume that the pattern of input stripes is sampled at the center of each pixel. The resulting pattern has a much wider spacing. Aliasing can cause all kinds of unwanted effects. Patterns that should be invisible because they are beyond the resolving power of the human eye can become all too visible. Patterns that are unrelated to the original data can occur in Moiré fringes. This is surely the reason why the retinal mosaic of receptor cells is not regular except in small patches (Figure 2.16). Another aliasing effect is illustrated in Figure 2.30. The line shown in the top part of the figure becomes a staircase pattern when it is drawn using large pixels. The problem is that each pixel samples the line at a single point. Either that point is on the line, in which case the pixel is colored black, or it is not, in which case the pixel is colored white. A set of techniques known as *antialiasing* can help with this. Antialiasing consists of computing the *average* of the light pattern that is represented by each pixel. The result is shown in the lower part of Figure 2.30. Proper antialiasing can be a more cost-effective solution than simply increasing the number of pixels in the display. With it, a low-resolution display can be made as effective as a much higher resolution

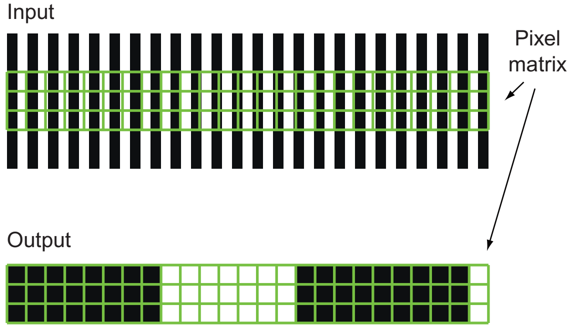


Figure 2.29 A striped pattern is sampled by pixels. The output is shown below.

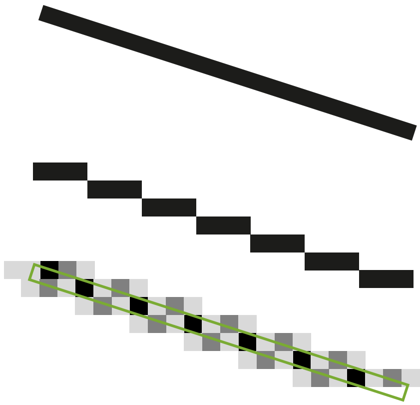


Figure 2.30 Aliasing artifacts with antialiasing as a solution.

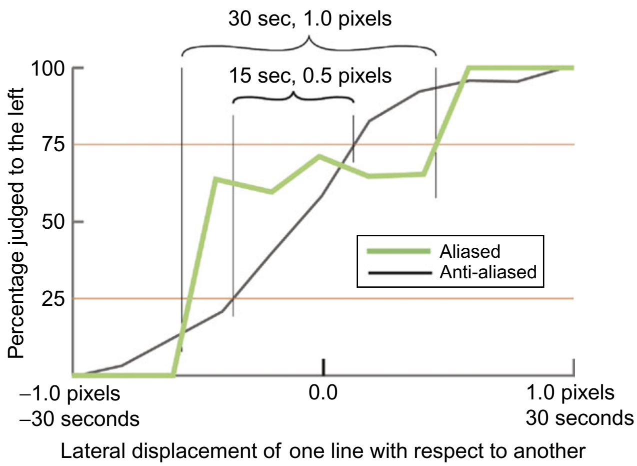


Figure 2.31 An aliased line that is not quite horizontal.

display, but it does require extra computation. Also, a full-color image requires properly antialiasing of the three color components, not just the brightness levels.

In data visualization, aliasing effects can sometimes actually be useful; for example, it is much easier to judge whether a line is perfectly horizontal on the screen with aliasing than without it (Figure 2.31). Because of our ability to see very small line displacements (vernier acuity), aliasing makes small misalignments completely obvious. The spatial frequency amplification illustrated in Figure 2.29 can be used as a deliberate technique to magnify certain kinds of regular patterns to make invisibly fine variations visible (Post et al., 1997). It is used in optics to judge the sphericity of mirrors and lenses.

Number of Dots

The main reason why we need 1200 dots per inch on a laser printer is that the dots of a laser printer are either black or white; to represent gray, many dots must be used. Essentially, one pixel is made up of many dots. Thus, for example, a 16×16 matrix of dots can be used to generate 257 levels of gray because from 0 to 256 of the dots can be colored black. In practice, square patches are not used, because these cause aliasing problems. To correct aliasing effects, randomness is used in distributing the dots, and errors are propagated from one patch to neighboring patches. Most graphics textbooks provide an introduction to these techniques (e.g., Foley et al., 1990). The fact that grays are made from patterns of black and white dots means that the resolution of a laser printer actually is 1200 dots per inch only for black-and-white patterns. For gray patterns, the resolution is at least ten times lower.

> **[G2.11]** Antialias visualizations wherever possible, especially where regular patterns, fine textures, or narrow lines are being displayed.

Superacuities and Displays

Superacuities provide a reason why we might wish to have very high-resolution monitors. As discussed earlier, superacuities occur because the human visual system can integrate information from a number of retinal receptors to give better than receptor resolution; for example, in vernier acuity, better than 10 arc-second resolution is achievable. However, in my laboratory, we have obtained experimental evidence that antialiasing can result in superacuity performance on vernier acuity tasks. This involves making judgments to see differences in the alignment of fine lines that are actually smaller than individual pixels. Figure 2.32 shows data from an experiment

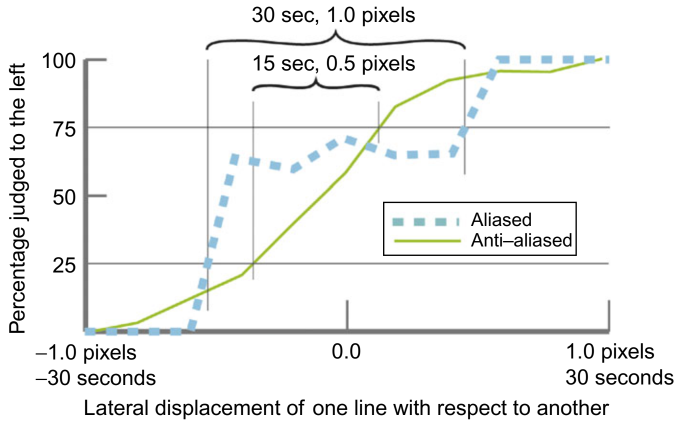


Figure 2.32 Results from an experiment showing that vernier acuity can be improved by antialiasing. The threshold is defined as half the horizontal difference between the 25% threshold and the 75% threshold.

that my research assistant, Tim Millar, and I carried out to determine whether vernier acuity performance can be achieved to higher than pixel resolution if the lines are antialiased. In the standard vernier acuity task, subjects judge whether one vertical line is above or below another, as in Figure 2.17(d), although we did it with vertical lines displaced laterally instead. The purpose of the experiment was to determine how small a displacement can be perceived more than 50% of the time. In our study, one line was displaced horizontally by an amount that varied randomly in a range between 1 pixel and –1 pixel, corresponding to ±30 seconds of arc at the viewing distance we chose. The question asked was, "Is the lower line to the right of the upper line?" The percentage correct was computed based on the answers given over a large number of trials. By convention, vernier acuity is defined as half the difference between 25% correct performance and 75% correct performance. In Figure 2.32, two of our results are shown for aliased and antialiased lines. The actual threshold is half of each range on the *x*-axis. Thus, Figure 2.32 shows a 15 second vernier acuity threshold (30 seconds × 0.5) for aliased lines and a 7.5 second threshold (15 seconds × 0.5) for antialiased lines. This data shows that, given proper antialiasing, superacuity performance to better than pixel resolution can be achieved.

Temporal Requirements of the Perfect Display

Just as we can evaluate the spatial requirements for a perfect monitor, so can we evaluate the temporal requirements. The limit of resolution that most of us can perceive is about 50-Hz flicker; hence, the 50- to 75-Hz refresh rate of the typical monitor would seem to be adequate. However, temporal aliasing artifacts are common in computer graphics and movies. The "reversing wagon wheel" effect is the one most often noticed (the wheel of a wagon in a western movie appears to rotate in the wrong direction). Temporal aliasing effects are especially pronounced when the image update rate is low, and it is common in data visualization systems to have animated images that are updated only about 10 times per second even though the screen is refreshed at 60 Hz or better. An obvious result is the breaking up of a moving object into a series of discrete objects. If the data contains a repetitive temporal pattern, aliasing and sampling effects can occur that are the analogs of the spatial aliasing effects. Sometimes a single object can appear to be multiple objects. To correct these problems, temporal antialiasing can be employed. Part of a moving image may pass through several pixels over the course of a single animation frame. The correct antialiasing solution is to color each pixel according to the percentage contributions of all the different objects as they pass through it for the duration of the animation frame. Thus, if the refresh rate is 60 Hz, a program must calculate the *average* color for each pixel that is affected by the moving pattern for each 1/60-second interval. This technique is often called *motion blur*. It can be computationally expensive in practice and is rarely done except in the case of high-quality animations created for the movie industry. As computers become faster, we can expect antialiasing to be more widely used in data visualization, because there is no doubt that aliasing effects can be visually disturbing and occasionally misleading.

Conclusion

In comparison with the richness of the visual world, the computer screen is simple indeed. It is remarkable that we can achieve so much with such a limited device. In the world, we perceive subtly textured, visually rich surfaces, differentiated by shading, depth-of-focus effects, and texture gradients. The computer screen merely produces a two-dimensional array of colors. Gibson's concept of the ambient optical array, introduced at the beginning of this chapter, provides a context for understanding the success of this device, despite its shortcomings. Given a particular direction and a viewing angle of 20 degrees or so, a computer monitor is capable of reproducing many (but not all) of those aspects of the ambient array that are most important to perception. As discussed in Chapter 4, this is especially true in the realm of color, where a mere three colors are used to effectively reproduce much of the gamut to which humans are sensitive. Spatial information, in the form of texture gradients and other spatial cues, is also reproducible to some extent on a monitor; however, there are problems in the reproduction of fine texture. The actual pixel pattern may provide a texture that visually competes with the texture designed for display. As discussed in Chapter 5, this represents a serious shortcoming when we wish to use texture as a display option.

A typical monitor only stimulates perhaps 5 to 10% of the visual field at normal viewing distances, as shown in Figure 2.18. This is not as serious a shortcoming as it might seem, because the central field of view is heavily overweighted in human visual processing. In fact, looking at the center of a monitor screen from a normal viewing distance stimulates considerably more than 50% of the visual processing mechanisms in the brain.

If we wish to create artificial virtual-reality displays as a method for presenting visual data, current displays have serious problems. One of these is their lack of ability to provide focal depth-of-focus information. In the real world, the eye must refocus on objects at different distances. Because this is not the case for computer graphics presented on the screen, it can confuse our spatial processing systems. This problem will be discussed further in Chapter 7 under the heading "The Vergence–Focus Problem."

Fortunately, the most important pattern perception mechanisms for data visualization operate in two dimensions, not three. The value of VR approaches has yet to be demonstrated although the naïve assumption that interactive 3D must be better has caused much squandering of money and resources. The good news is that we can achieve almost everything that is important without recourse to radical new technologies.

CHAPTER THREE

Lightness, Brightness, Contrast, and Constancy

It would be dull to live in a gray world, but we would actually get along just fine 99% of the time. Technically, we can divide color space into one luminance (gray scale) dimension and two chromatic dimensions. It is the luminance dimension that is most basic to perception. Understanding it can help us answer practical questions: How do we map data to a gray scale? How much information can we display per unit area? How much data can we display per unit time? Can gray scales be misleading? (The answer is "yes.")

To understand the applications of gray scales we need to address other, more fundamental questions: How bright is a patch of light? What is white? What is black? What is a middle gray? These are simple-sounding questions, but the answers are complex and lead us to many of the basic mechanisms of perception. The fact that we have light-sensing receptors in our eyes might seem like a good starting point, but individual receptor signals tell us very little. The nerves that transmit information from the eyes to the brain transmit nothing about the amount of light falling on the retina. Instead, they signal the *relative* amount of light: how a particular patch of light differs from a neighboring patch, or how a particular patch of light has changed in the past instant. Neurons processing visual information in the early stages of the retina and primary visual cortex do not behave like light meters; they act as *change* meters.

The signaling of differences is not special to lightness and brightness; it is a general property of many early sensory systems, and we will come across it again and again throughout this book. The implications are fundamental to the way we perceive information. The fact that differences, not absolute values, are transmitted to the brain

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accounts for contrast illusions that can cause substantial errors in the way data is "read" from a visualization. The signaling of differences also means that the perception of lightness is nonlinear, and this has implications for the gray-scale coding of information. But, to belabor the occasional inaccuracies of perception does not do justice to millions of years of evolution. The fact that the early stages of vision are nonlinear does not mean that all perception is inaccurate. On the contrary, we can usually make quite sophisticated judgments about the lightness of *surfaces* in our environments. This chapter shows how simple, early visual mechanisms can help our brains do sophisticated things, such as perceive the surface colors of objects correctly no matter what the illumination level.

This chapter is also the first part of a presentation of color vision. Luminance can be regarded as but one of three color dimensions, albeit the most important one. Discussing this dimension in isolation gives us an opportunity to examine many of the basic concepts of color with a simpler model. (This is expanded in Chapter 4 into a full three-color-channel model.) We start by introducing properties of neurons including the concept of the *visual receptive field*, together with a number of display distortion effects that can be explained by simple neural models. The bulk of this chapter is taken up with a discussion of the concepts of luminance, lightness, and brightness and the implications of these for data display.

The practical lessons of this chapter are related to the way data values can be mapped to gray values using gray-scale coding. The kinds of perceptual errors that can occur owing to simultaneous contrast are discussed at length. More fundamentally, the reasons why the visual system makes these errors provide a general lesson. The nervous system works by computing difference signals at almost every level. The lesson is that visualization is not good for representing precise absolute numerical values, but rather for displaying patterns of differences or changes over time, to which the eye and brain are extremely sensitive.

Neurons, Receptive Fields, and Brightness Illusions

Neurons are the basic circuits of information processing in the brain. In some respects, they are like transistors, only much more complex. Like the digital circuits of a computer, neurons respond with discrete pulses of electricity. But, unlike transistors, neurons are connected to hundreds and sometimes thousands of other neurons. Much of our knowledge about the behavior of neurons comes from single-cell recording techniques where a tiny microelectrode is inserted into a cell in the brain of a live animal and the cell's electrical activity is monitored as various patterns are displayed in front of its eyes. This research revealed that most neurons are constantly active, emitting pulses of electricity through connections with other cells. Depending on the visual pattern shown to the animal, the rate of firing can be increased or decreased as the neuron is excited or inhibited. Neuroscientists often set up amplifiers and loudspeakers in their laboratories so that they can hear the activity of cells that are being probed. The sound is like the clicking of a Geiger counter, becoming rapid when the cell is excited and slowing when it is inhibited.

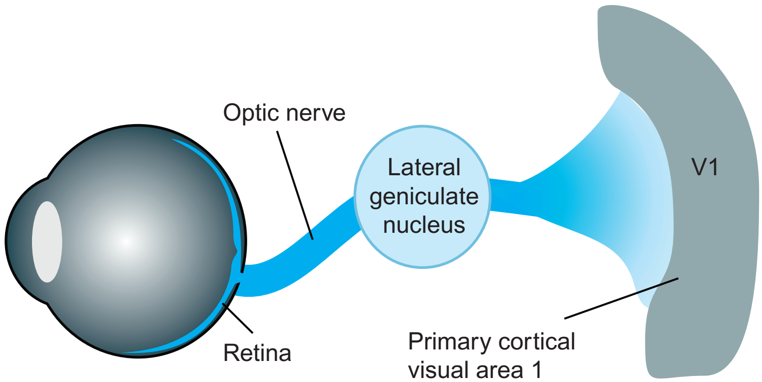

Figure 3.1 Signals from the retina are transmitted along the optic nerve to the lateral geniculate nucleus. From there, they are distributed to a number of areas, but mostly to visual area 1 of the cortex, located at the back of the head.

There is considerable neural processing of information in the eye itself. Several layers of cells in the eye culminate in retinal ganglion cells. These ganglion cells send information through the optic nerve via a way station, called the *lateral geniculate nucleus*, on to the primary visual processing areas at the back of the brain, as shown in Figure 3.1.

The *receptive field* of a cell is the visual area over which a cell responds to light. This means that patterns of light falling on the retina influence the way the neuron responds, even though it may be many synapses removed from receptors. Retinal ganglion cells are organized with circular receptive fields, and they can be either on-center or off-center. The activity of an on-center cell is illustrated in Figure 3.2. When this kind of cell is stimulated in the center of its receptive field, it emits pulses at a greater rate. When the cell is stimulated outside of the center of its field, it emits pulses at a lower than normal rate and is said to be inhibited. Figure 3.2 also shows the output of an array of such neurons being stimulated by a bright edge. The output of this system is an enhanced response on the bright side of the edge and a depressed response on the dark side of the edge, with an intermediate response to the uniform areas on either side. The cell fires more on the bright side because there is less light in the inhibitory region; it is less inhibited.

A widely used mathematical description of the concentric receptive field is the difference of Gaussians model (often called the DoG function):

$$f(x) = \alpha_1 e^{-\left(\frac{x}{w_1}\right)^2} - \alpha_2 e^{-\left(\frac{x}{w_2}\right)^2} \tag{3.1}$$

In this model, the firing rate of the cell is the difference between two Gaussians. One Gaussian represents the center and the other represents the surround, as illustrated in Figure 3.3. The variable x represents the distance from the center of the field, w_1 defines the width of the center, and w_2 defines the width of the surround. The amount

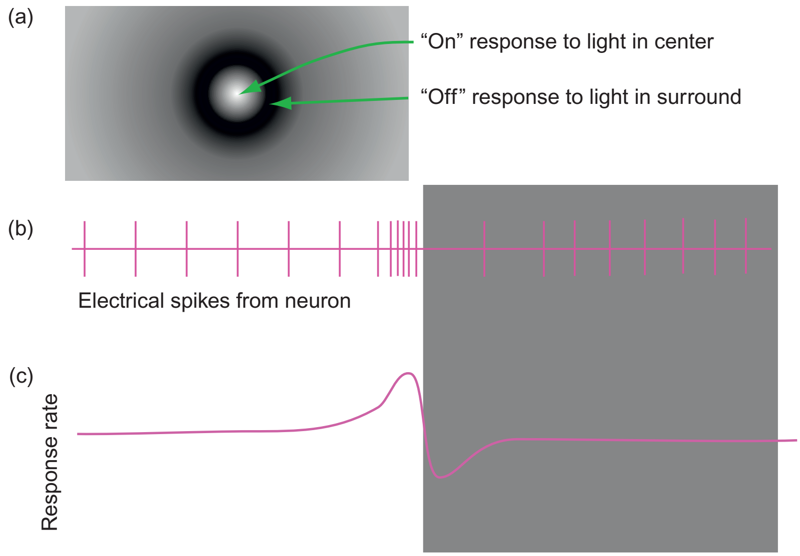

Figure 3.2 (a) The receptive field structure of an on-center simple lateral geniculate cell. (b) As the cell passes over from a light region to a dark region, the rate of neural firing increases just to the bright side of the edge and decreases on the dark side. (c) A smoothed plot of the cell activity level.

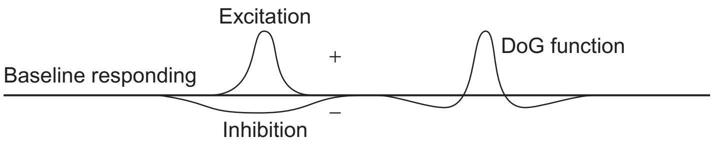

Figure 3.3 Difference of Gaussians (DoG) model of a receptive field.

of excitation or inhibition is given by the amplitude parameters α_1 and α_2. The DoG function and the concentric receptive field are an example of lateral inhibition in action. Stimulation of receptors at the edge of the field *laterally inhibit* the response at the center.

We can easily calculate how a DoG type of receptor responds to various patterns. We can either think of the pattern passing over the receptive field of the cell or think of the output of a whole array of DoG cells arranged in a line across the pattern. When we use a computer to simulate either operation, we discover that the DoG receptive field can be used to explain a variety of brightness contrast effects.

In the Hermann grid illusion, shown in Figure 3.4, black spots appear at the intersections of the bright lines. The explanation is that there is more inhibition at the spaces between two squares, so they seem brighter than the regions at the intersections.

Simultaneous Brightness Contrast

The term *simultaneous brightness contrast* is used to explain the general effect whereby a gray patch placed on a dark background looks lighter than the same gray patch on a light background. Figure 3.5 illustrates this effect and the way it is predicted by the DoG model of concentric opponent receptive fields.

Figure 3.4 Hermann grid illusion. The black spots that are seen at the intersections of the lines are thought to result from the fact that there is less inhibition when a receptive field is at position (a) than at position (b).

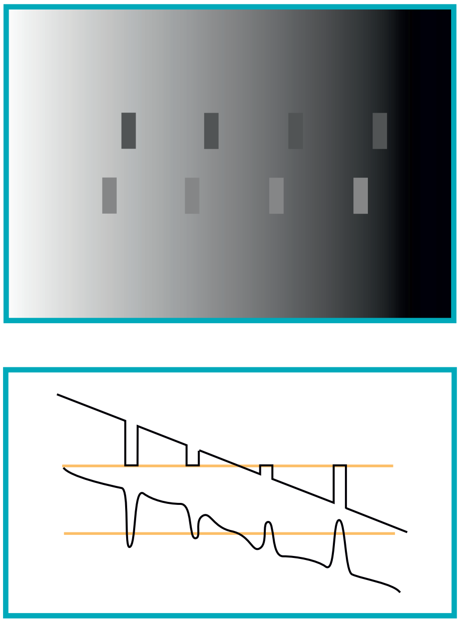

Figure 3.5 Illustration of simultaneous brightness contrast. The upper row contains rectangles of an identical gray. The lower rectangles are a lighter gray, also identical. The graph below illustrates the effect of a DoG filter applied to this pattern.

Mach Bands

Figure 3.6 demonstrates a Mach band effect. At the point where a uniform area meets a luminance ramp, a bright band is seen. In general, Mach bands appear where there is an abrupt change in the first derivative of a brightness profile. The lower plot on the right shows how this is simulated by a DoG model.

The Chevreul Illusion

When a sequence of gray bands is generated as shown in Figure 3.7, the bands appear darker at one edge than the other, even though they are uniform. The diagram to the right in Figure 3.7 shows that this visual illusion can be simulated by the application of a DoG model of the neural receptive field.

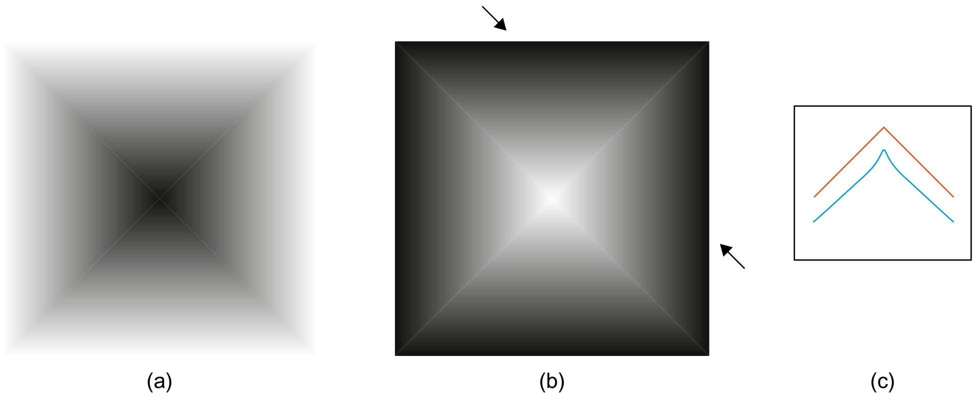

Figure 3.6 Illustration of Mach banding. (a, b) Dark and bright Mach bands are evident at the boundaries between the internal triangles. (c) The red curve shows the actual brightness profile between the two arrows. The blue curve shows how the application of a DoG filter models the bright bands that are seen.

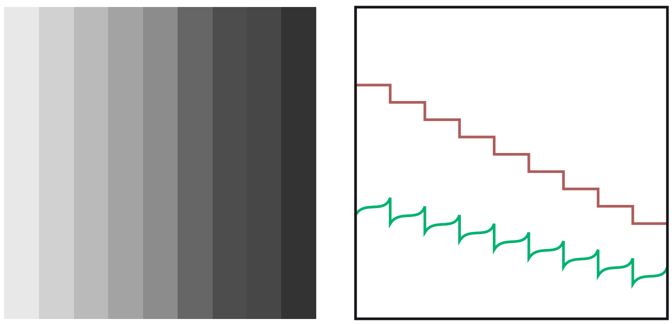

Figure 3.7 The Chevreul illusion. The measured lightness pattern is shown by the staircase pattern on the right. What is perceived can be closely approximated by a DoG model. The lower plot on the right shows the application of a DoG filter to the staircase pattern shown above.

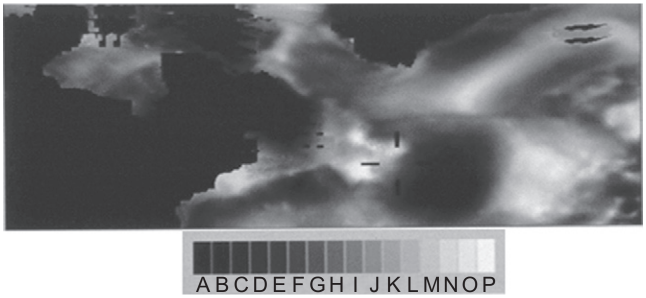

Figure 3.8 A gravity map of the North Atlantic Ocean. Large errors occur when gray-scale maps are read using a key. (*From Ware (1988). Reproduced with permission.*)

Simultaneous Contrast and Errors in Reading Maps

Simultaneous contrast effects can result in large errors of judgment when reading quantitative (value) information displayed using a gray scale (Cleveland & McGill, 1983); for example, Figure 3.8 shows a gravity map of part of the North Atlantic Ocean where the local strength of the gravitational field is encoded in shades of gray. In an experiment to measure the effects of contrast on data encoded in this way, we found substantial errors averaging 20% of the entire scale (Ware, 1988). The contrast in this case comes from the background of the gray scale itself and the regions surrounding any designated sampling point. Better schemes for displaying scalar maps using color in addition to lightness scaling are discussed in Chapter 4.

> **[G3.1]** Avoid using gray scale as a method for representing more than a few (two to four) numerical values.

Contrast Effects and Artifacts in Computer Graphics

One of the consequences of Mach bands, and of contrast effects in general, is that they tend to highlight the deficiencies in the common shading algorithms used in computer graphics. Smooth surfaces are often displayed using polygons, both for simplicity and to speed the computer graphics rendering process, the fewer the polygons the faster the object can be drawn. This leads to visual artifacts because of the way the visual system enhances the boundaries at the edges of polygons. Figure 3.9 shows three different shading methods applied to a sphere that has been constructed from four-sided polygons.

> ***Uniform shading.*** The light reflected from each polygonal facet is computed by taking into account the incident illumination and the orientation of the surface with respect to the light. The entire facet is then filled uniformly with the resulting color. Scanning across an object modeled in this way reveals stepwise changes in color. The steps are exaggerated, producing the Chevreul illusion.

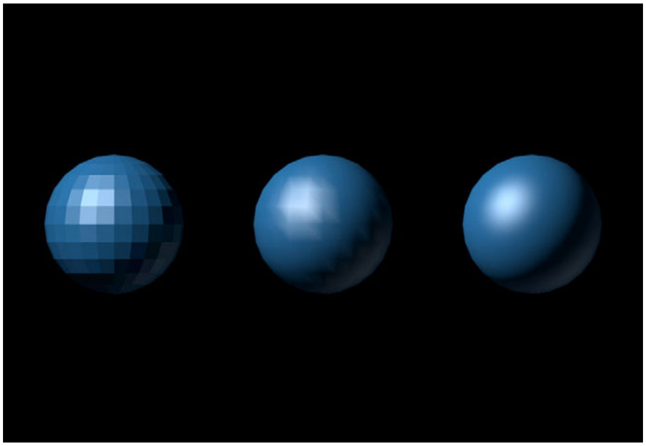

Figure 3.9 Three different shading methods used in computer graphics. Flat shading on the left is subject to the Chevreul illusion. Gouraud shading in the center results in Mach banding. Phong shading, on the right, produces something that looks smooth even though it is based on the same number of facets.

Gouraud shading. A shading value is calculated not for the facets but for the edges between the facets. This is done by averaging the surface normals at the boundaries where facets meet. As each facet is painted during the rendering process, the color is linearly interpolated between the facet boundaries. Scanning across the object, we see linear changes in color across polygons, with abrupt transitions in gradient where the facets meet. Mach banding occurs at these facet boundaries, enhancing the discontinuities.

Phong shading. As with Gouraud shading, surface normals are calculated at the facet boundaries; however, in this case, the surface normal is interpolated between the edges. The result is smooth changes in lightness with no appreciable Mach banding.

Edge Enhancement

Lateral inhibition can be considered the first stage of an edge detection process that signals the positions and contrasts of edges in the environment. One of the consequences is that pseudoedges can be created; two areas that physically have the same lightness can be made to look different by having an edge between them that shades off gradually to the two sides (Figure 3.10). The brain does perceptual interpolation so that the entire central region appears lighter than surrounding regions. This is called the *Cornsweet effect*, after the researcher who first described it (Cornsweet, 1970).

Cornsweet style contours have a clear inside and outside, unlike regular lines. In some visualizations, what is inside and outside a bounded region can become unclear,

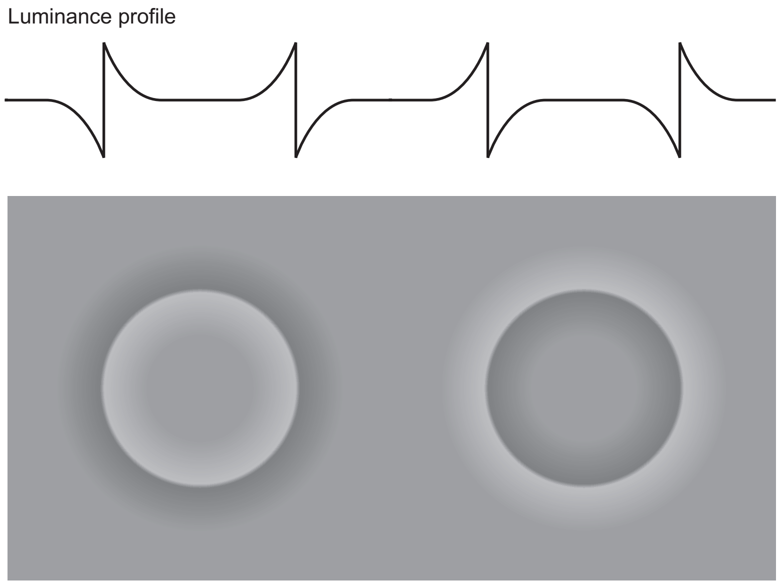

Figure 3.10 The Cornsweet effect. The curve above shows a horizontal luminance profile across the image below. The areas in the centers of the circles tend to look lighter than the surrounding area, even though they are actually the same shade. This provides evidence that the brain constructs surface color based largely on edge contrast information.

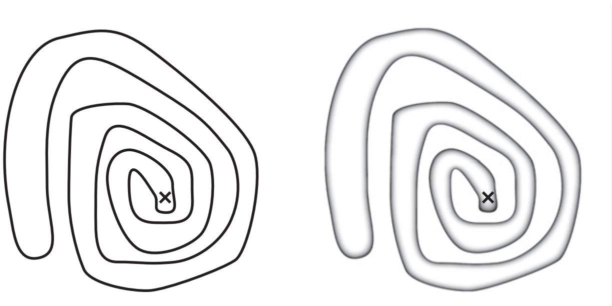

Figure 3.11 It is difficult to see if the X is inside or outside of the bounded region. Using a Cornsweet contour makes it possible to see the solution much more rapidly.

especially if the boundary is convoluted. Figure 3.11 demonstrates that Cornsweet contours can solve the problem. Alternative methods for defining complex regions are color or texture fills.

> **[G3.2]** Consider using Cornsweet contours instead of simple lines to define convoluted bounded regions.

The enhancement of edges is also an important part of some artists' techniques. It is a way to make objects more clearly distinct, given the limited dynamic range of paint. The example given in Figure 3.12 is from Seurat's painting of bathers. The same idea can be used in visualization to make areas of interest stand out. Figure 3.13(b) is a representation of a node–link diagram where the background has been adjusted to make critical subgraphs more distinct. This method is sometimes called *haloing*.

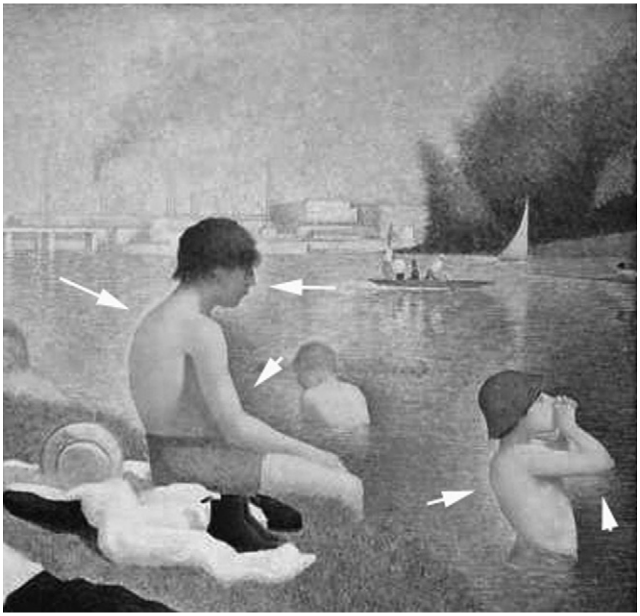

Figure 3.12 Seurat deliberately enhanced edge contrast to make his figures stand out.

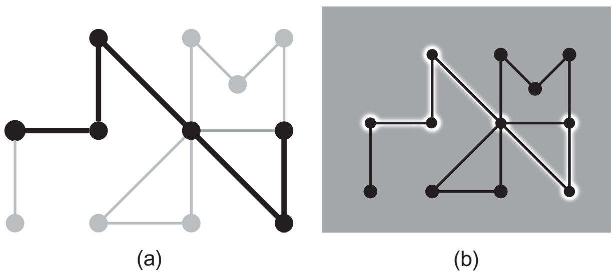

Figure 3.13 Two methods for highlighting a node–link diagram. (a) The contrast is reduced for the less important parts of the network. (b) The background contrast is increased using haloing to emphasize important parts.

[G3.3] Consider using adjustments in luminance contrast as a highlighting method. It can be applied by reducing the contrast of unimportant items or by locally adjusting the background to increase the luminance contrast of critical areas.

It is worth emphasizing that it is not the amount of light that leads to visual distinctness, but the amount of luminance contrast that occurs with the background. Black on white is as distinctive as white on black.

Luminance, Brightness, Lightness, and Gamma

Contrast effects may cause annoying problems in the presentation of data, but a deeper analysis shows that they can also be used to reveal the mechanisms underlying normal perception. How the contrast mechanism works to enable us to perceive our environment accurately, under all but unusual circumstances, is the main subject of the discussion that follows. The severe illusory contrast effects in computer displays are mostly a consequence of the impoverished nature of those displays, not of any inadequacy of the visual system.

It should now be evident that the perceived brightness of a particular patch of light has almost nothing to do with the amount of light coming from that patch as we might measure it with a photometer. Thus, what might seem like a simple question—"How bright is that patch of light?"—is not at all straightforward. To understand some of the issues involved we start with an ecological perspective, then consider perceptual mechanisms, and finally discuss applications in visualization.

Constancies

In order to survive, we need to be able to manipulate objects in the environment and determine their properties. Generally, information about the quantity of illumination is of very little use to us. Illumination is a prerequisite for sight, but otherwise we do not need to know whether the light we are seeing by is dim because it is late on a cloudy day or brilliant because of the noonday sun. What we do need to know about are objects—food, tools, plants, animals, other people, and so on—and we can find out a lot about objects from their surface properties. In particular, we can obtain knowledge of the spectral reflectance characteristics of objects—what we call their *color* and *lightness*. The human vision system evolved to extract information about surface properties of objects, often at the expense of losing information about the quality and quantity of light entering the eye. This phenomenon, the fact that we experience colored surfaces and not colored light, is called *color constancy*. When we are talking about the apparent overall reflectance of a surface, it is called *lightness constancy*. Three terms are commonly used to describe the general concept of quantity of light:

luminance, *brightness*, and *lightness*. The following brief definitions precede more extensive descriptions:

> ***Luminance*** is the easiest to define; it refers to the *measured amount of light* coming from some region of space. It is measured in units such as candelas per square meter. Of the three terms, only luminance refers to something that can be physically measured. The other two terms refer to psychological variables.
>
> ***Brightness*** generally refers to the *perceived amount of light* coming from a source. In the following discussion, it is used to refer only to things that are perceived as self-luminous. Sometimes people talk about bright colors, but *vivid* or *saturated* are better terms.
>
> ***Lightness*** generally refers to the *perceived reflectance of a surface*. A white surface is light. A black surface is dark. The shade of paint is another concept of lightness.

Luminance

Luminance is not a perceptual quantity at all. It is a physical measure used to define an amount of light in the visible region of the electromagnetic spectrum. Unlike lightness and brightness, luminance can be read out directly from a scientific measuring instrument. Luminance is a measurement of light energy weighted by the spectral sensitivity function of the human visual system.

We are about 100 times less sensitive to light at 450 nanometers than we are to light at 510 nanometers, and it is clearly important to take this difference into account when we are measuring light levels with human observers in mind. The human spectral sensitivity function is illustrated in Figure 3.14 and given at 10-nm intervals in Table 3.1. This function is called the $V(\lambda)$ function, where λ represents wavelength. It is an

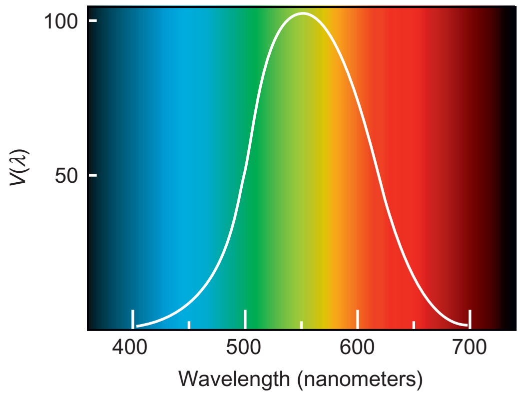

Figure 3.14 The CIE $V(\lambda)$ function representing the relative sensitivity of the human eye to light of different wavelengths.

Table 3.1 V(*λ*) *Function*

λ(nm)	Sensitivity	λ(nm)	Sensitivity	λ(nm)	Sensitivity
400	.0004	510	.5030	620	.3810
410	.0012	520	.7100	630	.2650
420	.0040	530	.8620	640	.1750
430	.0116	540	.9540	650	.1070
440	.0230	550	.9950	660	.0610
450	.0380	560	.9950	670	.0320
460	.0600	570	.9520	680	.0170
470	.0910	580	.8700	690	.0082
480	.1390	590	.7570	700	.0041
490	.4652	600	.6310	710	.0010
500	.3230	610	.5030	720	.0005

Note: Luminance sensitivity as it varies with wavelength.

international standard maintained by the *Commission Internationale de l'Éclairage* (CIE). The $V(\lambda)$ function represents the spectral sensitivity curve of a standard human observer. To find the luminance of a light, we integrate the light distribution, $E(\lambda)$, with the CIE estimate of the human sensitivity function, $V(\lambda)$.

$$L = \int_{400}^{700} V_\lambda E_\lambda \delta\lambda \tag{3.2}$$

When multiplied by the appropriate constant, the result is luminance, L, in units of candelas per square meter. Note that a great many technical issues must be considered when we are measuring light, such as the configuration of the measuring instrument and the sample. Wyszecki and Stiles (1982) wrote an excellent reference. It is directly relevant to data display that the blue phosphor of a monitor has a peak at about 450 nm. Table 3.1 shows that at this wavelength human sensitivity is only 4% of the maximum in the green range. In Chapter 2, we noted that the chromatic aberration of the human eye means that a monitor's blue light is typically out of focus. The fact that we are also insensitive to this part of the spectrum is another reason why representing text and other detailed information using the pure blue of a monitor is not a good idea, particularly against a black background.

The $V(\lambda)$ function is extremely useful because it provides a close match to the combined sensitivities of the individual cone receptor sensitivity functions. It is reasonable to think of the $V(\lambda)$ function as measuring the luminance efficiency of the first stage of an extended process that ultimately allows us to perceive useful information such as surface lightness and the shapes of surfaces. Technically, it defines how the sensitivity of the so-called *luminance channel* varies with wavelength.

The luminance channel is an important theoretical concept in vision research; it is held to be the basis for most pattern perception, depth perception, and motion perception. In Chapter 4, the properties of the luminance channel are discussed in more detail in comparison to the color processing *chrominance* channels.

Displaying Details

As the spatial modulation sensitivity function shows (see Figure 2.26 in Chapter 2), the finer the detail, the greater the contrast required.

> **[G3.4]** Use a minimum 3:1 luminance contrast ratio between a pattern and its background whenever information is represented using fine detail, such as texture variation, small-scale patterns, or text.

This rule has been generalized from the International Standards Organization (ISO) guideline applying to text (ISO 9241, Part 3), but it is only a minimum; the ISO goes on to recommend that a 10:1 ratio is optimal for text, and the same can be said of any display of detail. Of course, this severely restricts the range of colors that can be used, but if the detail is critical this cannot be helped.

Brightness

The term *brightness* usually refers to the perceived amount of light coming from self-luminous sources. It relates to the perception of the brightness of indicator lights in an otherwise darkened display—for example, nighttime instrument displays in the cockpits of aircraft and on the darkened bridges of ships. Perceived brightness is a very nonlinear function of the amount of light emitted by a lamp. Stevens (1961) popularized a technique known as *magnitude estimation* to provide a way of measuring the perceptual impact of simple sensations. In magnitude estimation, subjects are given a stimulus, such as a patch of light viewed in isolation. They are told to assign this stimulus a standard value—for example, 10—to denote its brightness. Subsequently, they are shown other patches of light, also in isolation, and asked to assign them values relative to the standard that they have set. If a patch seems twice as bright as the reference sample, it is assigned the number 20; if it seems half as bright, it is assigned the number 5, and so on. Applying this technique, Stevens discovered that a wide range of sensations could be described by a simple power law:

$$S = aI^n \tag{3.3}$$

This law states that perceived sensation S is proportional to the stimulus intensity I raised to a power n. The power law has been found to apply to many types of sensations, including loudness, smell, taste, heaviness, force, and touch. The power law applies to the perceived brightness of lights viewed in the dark.

$$\textit{Perceived Brightness} = \textit{Luminance}^n \tag{3.4}$$

However, the value of n depends on the size of the patch of light. For circular patches of light subtending 5 degrees of visual angle, n is 0.333, whereas for point sources of light n is close to 0.5.

These findings are really only applicable to lights viewed in relative isolation in the dark. Although they have some practical relevance to the design of control panels to be viewed in dark rooms, many other factors must be taken into account in more complex displays. Before we go on to consider these perceptual issues, it is useful to know something about the way computer monitors are designed.

Monitor Gamma

Most visualizations are produced on monitor screens. Anyone who is serious about producing such a thing as a gray scale with perceptually equal steps, or color reproductions in general, must come to grips with the properties of computer monitors. The relationship of physical luminance to the input signal on a monitor is approximated by a gamma function:

$$L = V^{\gamma} \tag{3.5}$$

where V is the voltage driving one of the electron guns in the monitor, L is the luminance, and γ is an empirical constant that varies widely from monitor to monitor (values can range from 1.4 to 3.0). See Cowan (1983) for a thorough treatise on monitor calibration.

This monitor nonlinearity is not accidental; it was created by early television engineers to make the most of the available signal bandwidth. They made television screens nonlinear precisely because the human visual system is nonlinear in the opposite direction, as Stevens had observed. For example, a gamma value of 2.0 will exactly cancel a brightness power function exponent of 0.5, resulting in a display that produces a linear relationship between voltage and perceived brightness. Figure 3.15 illustrates this point. Most monitors have a gamma value of around 2.0.

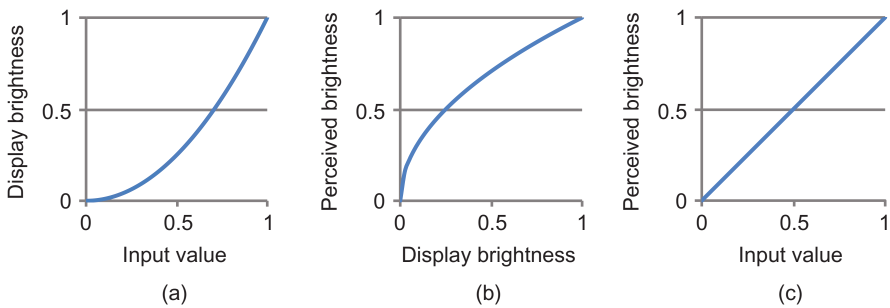

Figure 3.15 (a) On a computer display, the brightness increases faster than the input value. (b) Perceived brightness of a display varies in the opposite way. (c) The two effects cancel out.

Adaptation, Contrast, and Lightness Constancy

A major task of the visual system is to extract information about the lightness and color of objects despite a great variation in illumination and viewing conditions. It cannot be emphasized enough that luminance is completely unrelated to perceived lightness or brightness. If we lay out a piece of black paper in full sunlight on a bright day and point a photometer at it, we may easily measure a value of 1000 candelas for reflected light per square meter. A typical "black" surface reflects about 10% of the available light, so it would give a measurement of 100 candelas per square meter. If we now take our photometer into a typical office and point it at a white piece of paper, we will probably measure a value of about 50 candelas per square meter. Thus, a black object on a bright day in a beach environment may reflect to the eye much more light than white paper in an office. Even in the same environment, white paper lying under the boardwalk may reflect less light (be darker) than black paper lying in the sun. Nevertheless, we can distinguish black from white from gray (achieve lightness constancy) with ease.

Figure 3.16 illustrates the range of light levels we encounter, from bright sunlight to starlight. A normal interior will have an artificial illumination level of approximately 50 lux. (Lux is a measure of incident illumination that incorporates the $V(\gamma)$ function.) On a bright day in summer, the light level can easily be 50,000 lux. Except for the brief period of adaptation that occurs when we come indoors on a bright day, we are almost totally oblivious to this huge variation. Remarkably, our visual systems can achieve lightness constancy over virtually this entire range; in bright sunlight or moonlight, we can tell whether a surface is black, white, or gray.

The first-stage mechanism of lightness constancy is *adaptation*. The second stage of level invariance is *lateral inhibition*. Both mechanisms help the visual system to factor out the effects of the amount and color of the illumination.

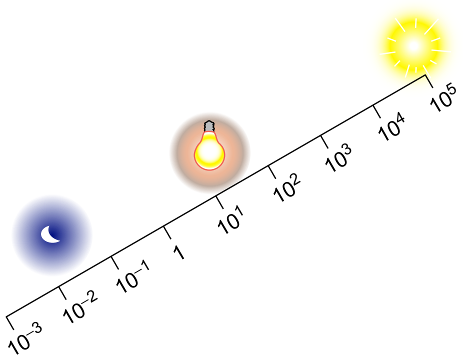

Figure 3.16 The eye/brain system is capable of functioning over a huge range of light levels. The amount of light available on a bright day at the beach is 10,000 times greater than the light available in a dimly lit room.

The role of adaptation in lightness constancy is straightforward. The changing sensitivity of the receptors and neurons in the eye helps factor out the overall level of illumination. One mechanism is the bleaching of photopigment in the receptors themselves. At high light levels, more photopigment is bleached and the receptors become less sensitive. At low light levels, photopigment is regenerated and the eyes regain their sensitivity. This regeneration can take some time, which is why we are briefly blinded when coming into a darkened room out of bright sunlight. It can take up to half an hour to develop maximum sensitivity to very dim light, such as moonlight. In addition to the change in receptor sensitivity, the iris of the eye opens and closes. This modulates the amount of light entering the pupil but is a much less significant factor than the change in receptor sensitivity. In general, adaptation allows the visual system to adjust overall sensitivity to the ambient light level.

Contrast and Constancy

Contrast mechanisms, such as the concentric opponent receptive fields discussed previously, help us achieve constancy by signaling differences in light levels, especially at the edges of objects. Consider the simple desktop environment illustrated in Figure 3.17. A desk lamp, just to the right of the picture, has created nonuniform illumination over a wooden desk that has two pieces of paper lying on it. The piece nearer the lamp is a medium gray. Because it is receiving more light, it reflects about the same amount of light as the white paper, which is farther from the light. In the original environment, it is easy for people to tell which piece of paper is gray and which is white. Simultaneous contrast can help to explain this. Because the white paper is lighter relative to its background than the gray paper is relative to its background, the same mechanism that caused contrast in Figure 3.5 is responsible for enabling an accurate judgment to be made in this example. The illumination profile across the desk and the pieces of paper is similar to that illustrated in Figure 3.5, except that, in this case, contrast does not result in an illusion; instead, it helps us to achieve lightness constancy.

Contrast on Paper and on Screen

There is a subtlety here that is worth exploring. Paper reproductions of contrast and constancy effects are often less convincing than these effects are in the laboratory. Looking at Figure 3.17, the reader may well be excused for being less than convinced. The two pieces of paper may not look very different, but try the experiment with your own desk lamp and paper. Two holes punched in a piece of opaque cardboard can be used as a mask, enabling you to compare the brightness of the gray and white pieces of paper. Under these real-world viewing conditions, it is usually impossible to perceive the true relative luminance; instead, the surface lightness is perceived. But, take a photograph of the scene, like Figure 3.17, and the effect is less strong. It would be even weaker with a poorly printed gray image. Why is this? The answer lies in the

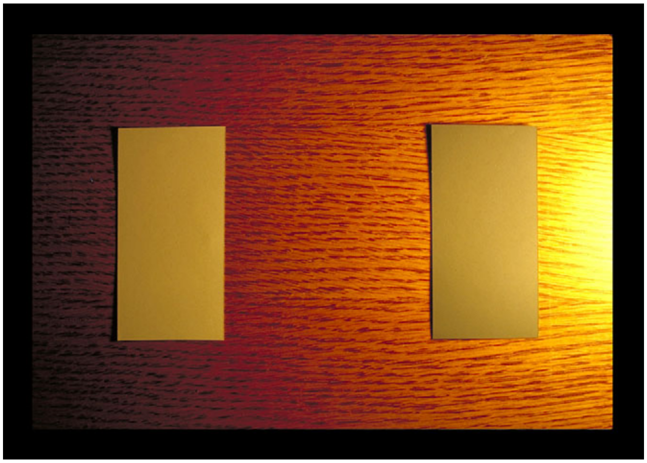

Figure 3.17 These two pieces of paper are illuminated by a desk lamp just to the right of the picture. This makes the amount of light reflected from the gray paper about the same as the light reflected from the white paper.

dual nature of pictures. The photograph itself has a surface, and to some extent we perceive the actual gray levels of the photographic pigment, as opposed to the gray levels of what is depicted. The poorer the reproduction, the more we see the actual color printed on the paper. A related effect occurs with depth perception and perspective pictures; to some extent we can see both the surface flatness and the three-dimensional (3D) layout of a depicted environment.

Contrast illusions are generally much worse in computer displays. On most screens there is no fine texture, except for the uniform pattern of pixels. Moreover, the screen is self-luminous, which may also confound our lightness constancy mechanisms. Scientists studying simultaneous contrast in the laboratory generally use perfectly uniform textureless fields and obtain extreme contrast effects—after all, under these circumstances, the only information is the differences between patches of light. Computer-generated virtual-reality images lie somewhere between real-world surfaces and the artificial featureless patches of light used in the laboratory in allowing the accurate perception of lightness.

How lightness is judged will depend on exactly how images are designed and presented. On the one hand, a monitor can be set up in a dark room and made to display featureless gray patches of light; in this case, simple contrast effects will dominate. However, if the monitor is used to simulate a very realistic 3D model of the environment, surface lightness constancies can be obtained, depending on the degree of realism, the quality of the display, and the overall setup. To obtain true virtual reality, the screen surface should disappear; to this end, some head-mounted displays contain diffusing screens that blur out the pixels and the dot matrix of the screen.

Perception of Surface Lightness

Although both adaptation and contrast can be seen as mechanisms that act in the service of lightness constancy, they are not sufficient. Ultimately, the solution to this perceptual problem can involve every level of perception. Three additional factors seem especially important. The first is that the brain must somehow take the direction of illumination and surface orientation into account in lightness judgments. A flat white surface turned away from the light will reflect less light than one turned toward the light. Figure 3.18 illustrates two surfaces being viewed, one turned away from the light and one turned toward it. Under these circumstances, people can still make reasonably accurate lightness judgments, showing that our brains can take into account both the direction of illumination and the spatial layout (Gilchrist, 1980).

The second important factor is that the brain seems to use the lightest object in the scene as a kind of reference white to determine the gray values of all other objects (Cataliotti & Gilchrist, 1995). This is discussed in the following section in the context of lightness scaling formulas, but first we must briefly mention the role of glossy highlights, something that is clearly important, though poorly understood.

The ratio of specular and nonspecular reflection can be important under certain circumstances. Figure 3.19 contains a picture of a world where everything is black and next to it a picture of a world in which everything is white. If we imagine these images as slides projected in a darkened room, it is obvious that every point on the black image is brighter than the surroundings in the room. How can we perceive something

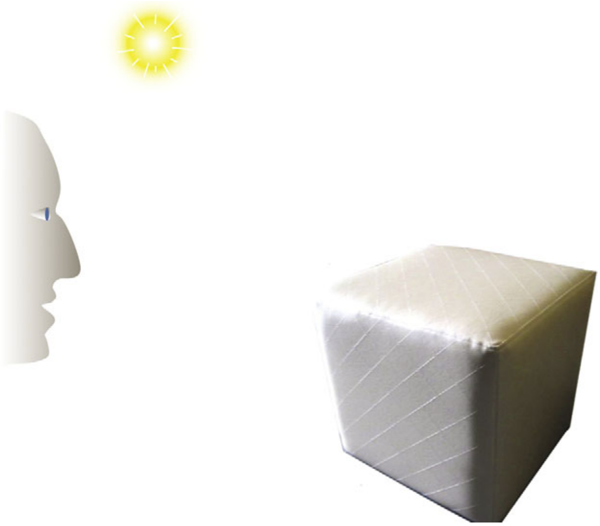

Figure 3.18 When making surface lightness judgments, the brain can take into account the fact that a surface turned away from the light receives less light than a surface turned toward the light.

(a) (b)

Figure 3.19 These two photographs show a scene in which everything is black and another where everything is white.

to be black when it is a bright image? In this case, the most important factor differentiating black from white is the ratio between the specular and the nonspecular reflected light. In the all-black world, the ratio between specular and nonspecular is much larger than in the all-white world.

Lightness Differences and the Gray Scale

Suppose that we wish to display map information using a gray scale. We might, for example, wish to illustrate the variability in population density within a geographical region or to produce a gravity map as shown in Figure 3.8. Ideally, for this kind of application, we would like a gray scale such that equal differences in data values are displayed as perceptually equally spaced gray steps (an interval scale). Such a scale is called a *uniform gray scale*. As we discussed earlier the gray scale is probably not the best way of coding this kind of information because of contrast effects (chromatic scales are generally better), but the problem does merit some attention because it allows us to discuss some fundamental and quite general issues related to perceptual scales.

Leaving aside contrast effects, the perception of brightness differences depends on whether lightness differences in a scene are small or large. At one extreme, we can consider the smallest difference that can be distinguished between two gray values. In this case, one of the fundamental laws of psychophysics applies. This is called *Weber's law*, after the 19th-century physicist Max Weber (Wyszecki & Stiles, 1982). Weber's law states that if we have a background with luminance L and superimpose on it a patch that is a little bit brighter ($L + \delta L$), then the value of δ that makes this small increment just visible is independent of the overall luminance. Thus, $\delta L/L$ is constant. Typically, under optimal viewing conditions, we can detect the brighter patch if δ is greater than about 0.005. In other words, we can just detect about a 0.5% change in brightness. Most computer graphics is done with just 256 gray levels (8 bits), and this is not quite sufficient to create a smooth gray sequence that varies in brightness by a factor of 100 from the darkest to the lightest with undetectable steps. Weber's law applies only to small differences. When large differences between gray samples are judged, many other factors become significant.

A typical experimental procedure used to study large differences involves asking subjects to select a gray value midway between two other values. The CIE has produced a uniform gray-scale standard based on a synthesis of the results from large numbers of experiments of this kind. This formula includes the concept of a reference white, although many other factors are still neglected.

$$L^* = 116(Y/Y_n)^{1/3} - 16 \tag{3.6}$$

where Y is the luminance of the color being judged, and Y_n is the luminance of a reference white in the environment, normally the surface that reflects most light to the eye. The result, L^*, is a value in a uniform gray scale. Equal measured differences on this scale approximate equal perceptual differences. It is reasonable to assume that $Y/Y_n > 0.01$, because even the blackest inks and fabrics still reflect more than 1% of incident illumination. This standard is used by the paint and lighting industries to specify such things as color tolerances. Equation 3.6 is part of the CIE LUV uniform color space standard, which is described more fully in Chapter 4.

Uniform lightness and color scales can only provide rough approximations. Because the perception of lightness is changed radically by many factors that are not taken into account by formulas such as Equation 3.6—perceived illumination, specular reflection from glossy surfaces, and local contrast effects—the goal of obtaining a perfect gray scale is not attainable. Such formulae should be taken as no more than useful approximations.

Contrast Crispening

Another perceptual factor that distorts gray values is called *contrast crispening* (see Wyszecki & Stiles, 1982). Generally, differences are perceived as larger when samples are similar to the background color. Figure 3.20 shows a set of identical gray scales on a range of different gray backgrounds. Notice how the scales appear to divide perceptually at the value of the background. The term *crispening* refers to the way more subtle gray values can be distinguished at the point of crossover. Crispening is not taken into account by uniform gray-scale formulas.

> **[G3.5]** If subtle gray-level gradations within the bounds of a small object are important, create low-luminance contrast between the object and its background.

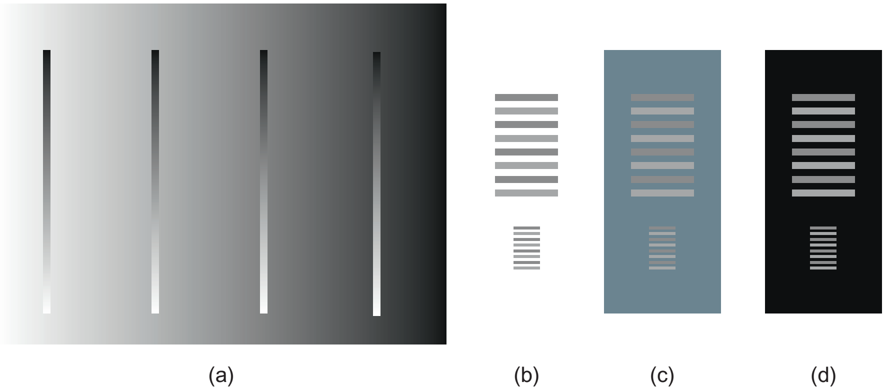

Figure 3.20 (a) All the gray strips are the same. Perceived differences between gray-scale values are enhanced where the values are close to the background gray value, an effect known as crispening. (b, c, d) The differences in the grays of the gray lattice are more evident (c) than with either the white (b) or the black (d) backgrounds, another example of crispening.

Monitor Illumination and Monitor Surrounds

In some visualization applications, the accurate perception of surface lightness and color is critical. One example is the use of a computer monitor to display wallpaper or fabric samples for customer selection. It is also important for graphic designers that colors be accurately perceived. To accomplish this, not only is it necessary to calibrate the monitor so that it actually displays the specified color range, but other factors affecting the state of adaptation of the user's eyes must also be taken into account. The color and the brightness of the surround of the monitor can be very important in determining how screen objects appear. The adaptation effect produced by room lighting can be equally important.

How should the lighting surrounding a monitor be set up? A monitor used for visual displays engages only the central part of the visual field, so the overall state of adaptation of the eye is maintained at least as much by the ambient room illumination. This means that the amount of light reflected from the walls of the room and other surfaces should not be too dissimilar to the amount of light coming from the screen, especially if the screen is small. There are other reasons for maintaining a reasonably high level of illumination in a viewing room, such as the ability to take notes and see other people. When people spend lots of time in dimly lit work environments, it can cause depression and reduced job satisfaction (Rosenthal, 1993); however, a side effect of a high level of room illumination is that some light falls on the monitor screen and is scattered back to the eye, degrading the image. In fact, under normal office conditions, between 5% and 20% of the illumination coming to the eye from the monitor screen will come indirectly from the room light, not from the luminous screen pixels. With projectors the situation is worse, because the white projector screen necessarily has a high reflectance, meaning that it will reflect room illumination.

[G3.6] Ideally, when setting up a monitor for viewing data, a light neutral-colored wall behind the screen should reflect an amount of light comparable to the level of light coming from the monitor. The wall facing the screen should be of low reflectance (mid- to dark gray) to reduce reflections from the monitor screen. Lights should be placed so that they do not reflect from the monitor screen.

[G3.7] When setting up a room for a projection system, ensure that minimal room light falls on the projector screen. This can be done by means of baffles to shield the screen from direct illumination. Low-reflectance (mid- to dark gray) walls are also desirable, as the walls will scatter light, some of which inevitably reaches the screen.

Figure 3.21 shows a monitor display with a shadow lying across its face. Although this is a rather extreme example, the effects are clear. Overall contrast is much reduced where the room light falls on the display. We can model the effects of illumination on a monitor by adding a constant to Equation 3.6:

$$L = V^{\gamma} + A \tag{3.7}$$

where A is the ambient room illumination reflected from the screen, V is the voltage to the monitor, and L is the luminance output for a given gamma.

If we wish to create a monitor for which equal voltage steps result in equal perceptual steps under conditions where ambient light is reflected, a lower gamma value is needed. Figure 3.22 shows the effects of different gamma values, assuming that 15% of the light coming from the screen is reflected ambient light. The CIE equation (Equation 3.6) has been used to model lightness scaling. As you can see, under these assumptions, a monitor is a perceptually more linear device with a gamma of only 1.5 than with a gamma of 2.5 (although under dark viewing conditions, a higher gamma is needed).

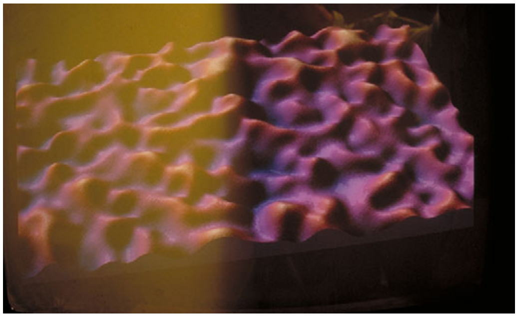

Figure 3.21 A monitor with a shadow falling across the left-hand side. Under normal viewing conditions, a significant proportion of the light coming from a screen is reflected ambient room illumination.

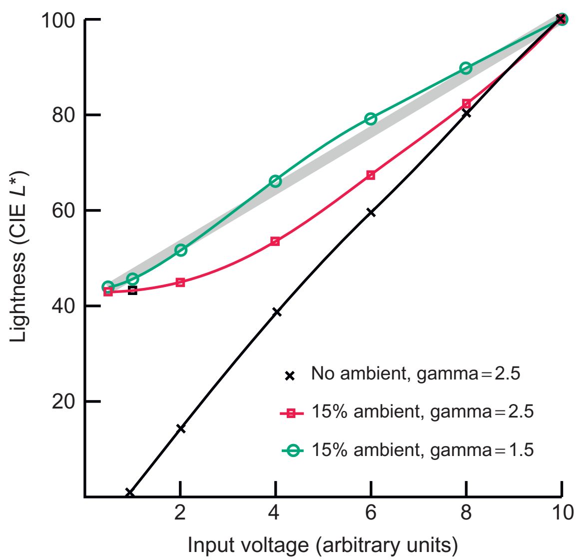

Figure 3.22 The three curves show how monitor gun voltage is transformed into lightness, according to the CIE model, with different amounts of ambient light reflected from the screen and different gamma settings.

If you cover part of your monitor screen with a sheet of white paper, under normal working conditions (when there are lights on in the room), you will probably find that the white of the paper is very different from the white of the monitor screen. The paper may look relatively blue or yellow, and it may appear darker or lighter. There are often large discrepancies between monitor colors and colors of objects in the surrounding environment.

For the creation of an environment where computer-generated colors are comparable to colors in a room, the room should have a standard light level and illuminant color. The monitor should be carefully calibrated and balanced so that the white of the monitor matches that of a sheet of white paper held up beside the screen. In addition, only a minimal amount of light should be allowed to fall on the monitor screen.

Figure 3.23 shows a computer display set up so that the lighting in the virtual environment shown on the monitor is matched with the lighting in the real environment surrounding the monitor. This was achieved by illuminating the region surrounding the monitor with a projector that contains a special mask. This mask was custom designed so that light was cast on the monitor casing and the desktop surrounding the computer, but no light at all fell on the part of the screen containing the picture. In addition, the direction and color of the light in the virtual environment were adjusted to exactly match the light from the projector. Simulated cast shadows were also created to match the cast shadows from the projector. Using this setup, it is possible to create a virtual environment whose simulated colors and other material

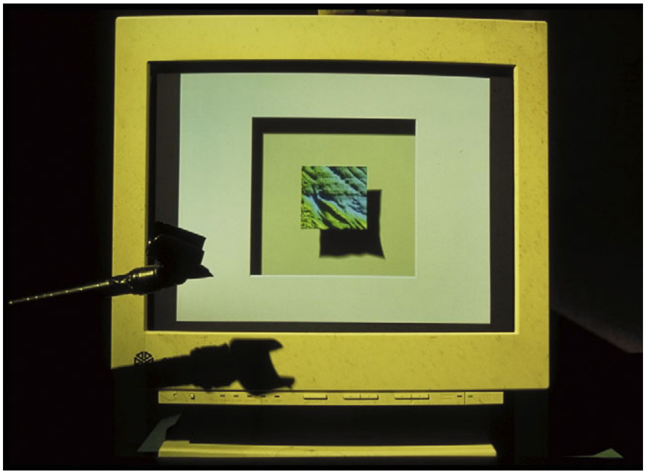

Figure 3.23 A projector was set up containing a mask specifically designed so that no light actually fell on the portion of the monitor screen containing the image. In this way, the illumination in the virtual environment displayed on the monitor was made to closely match the room illumination falling on the monitor frame and stand.

properties can be directly compared to the colors and material properties of objects in the room. (This work was done by Justin Hickey and the author.)

Conclusion

As a general observation, the use of gray-scale colors is not a particularly good method for categorically coding data (nominal scale). Contrast effects reduce accuracy, and the luminance channel of the visual system is fundamental to so much of perception (shape perception, in particular) that it is a waste of perceptual resources to use gray-scale encoding. Nevertheless, it is important to understand the problems of brightness and lightness perception because they point to issues that are fundamental to all perceptual systems. One of these basic problems is how perception works effectively in visual environments where the light level can vary by six orders of magnitude. The solution, arrived at over the course of evolution, is a system that essentially ignores the level of illumination. This may seem like an exaggeration—after all, we can certainly tell the difference between bright sunlight and dim room illumination—but we are barely aware of a change of light level on the order of a factor of 2. For example, in a room lit with a two-bulb fixture, it often goes unnoticed that one bulb has burned out, as long as the bulbs are hidden within a diffusing surround.

A fundamental point made in this chapter is the *relative* nature of low-level visual processing. As a general rule, nerve cells situated early in the visual pathway do not respond to absolute signals. Rather, they respond to differences in both space and time. At later stages in the visual system, more stable percepts such as the perception of surface lightness can emerge, but this is only because of sophisticated image analysis that takes into account such factors as the position of the light, cast shadows, and orientation of the object. The relative nature of lightness perception sometimes causes errors, but these errors are due mostly to a simplified graphical environment that confounds the brain's attempt to achieve surface lightness constancy. The mechanism that causes contrast errors is also the reason why we can perceive subtle changes in data values and can pick out patterns despite changes in the background light level.

Luminance contrast is an especially important consideration for choosing backgrounds and surrounds for a visualization. The way a background is chosen depends on what is important. If the outline shapes of objects are critical, the background should be chosen for maximum luminance contrast with foreground objects. If it is important to see subtle gradations in gray level, the crispening effect suggests that choosing a background in the midrange of gray levels will help us to see more of the important details.

Luminance is but one dimension of color space. In Chapter 4, this one-dimensional model is expanded to a three-dimensional color perception model. The luminance channel, however, is special. We could not get by without luminance perception, but we can certainly get by without color perception. This is demonstrated by the historic success of black-and-white movies and television. Later chapters describe how information encoded in the luminance channel is fundamental to perception of fine detail, discrimination of the shapes of objects through shading, stereoscopic depth perception, motion perception, and many aspects of pattern perception.

CHAPTER FOUR

Color

In the summer of 1997, I designed an experiment to measure human ability to trace paths between connected parts in a three-dimensional diagram. Then, as is my normal practice, I ran a pilot study in order to see whether the experiment was well constructed. By ill luck, the first person tested was a research assistant who worked in my lab. He had far more difficulty with the task than anticipated—so much so that I put the experiment back on the drawing board to reconsider, without trying any more pilot subjects. Some months later, my assistant told me he had just had an eye test and the optometrist had determined that he was color blind. This explained the problems with the experiment. Although it was not about color perception, I had marked the targets red in my experiment. He therefore had had great difficulty in finding them, which rendered the rest of the task meaningless. The remarkable aspect of this story is that my assistant had gone through 21 years of his life without knowing that he was blind to many color differences. This is not uncommon, and it strongly suggests that color vision cannot be all that important to everyday life. In fact, color vision is irrelevant to much of normal vision. It does not help us determine the layout of objects in space, how they are moving, or what their shapes are. It is not much of an overstatement to say that color vision is largely superfluous in modern life; nevertheless, color is extremely useful in data visualization.

Color vision does have a critical function, which is hardly surprising because this sophisticated ability must surely provide some evolutionary advantage. Color helps us break camouflage. Some things differ visually from their surroundings only by their color. An especially important example is illustrated in Figure 4.1. If we have color vision, we can easily see the cherries hidden in the leaves. If we do not, this

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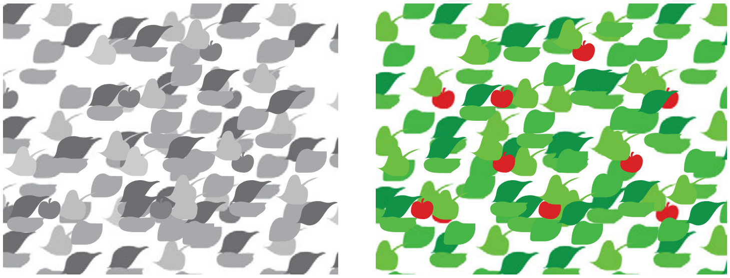

Figure 4.1 Finding the cherries is much easier with color vision.

becomes much harder. Color also tells us much that is useful about the material properties of objects. This is crucial in judging the condition of our food. Is this fruit ripe or not? It this meat fresh or putrid? What kind of mushroom is this? It is also useful if we are making tools. What kind of stone is this? Clearly, these can be life-or-death decisions. In modern hunter–gatherer societies, men are the hunters and women are the gatherers. This may have been true for long periods of human evolution, which could explain why it is mostly men who are color blind. If they had been gatherers, they would have been more than likely to eat poison berries—a selective disadvantage. In the modern age of supermarkets, these skills are much less valuable; this is perhaps why color deficiencies so often go unnoticed.

The role that color plays ecologically suggests ways that it can be used in information display. It is useful to think of color as an attribute of an object rather than as its primary characteristic. It is excellent for labeling and categorization, but poor for displaying shape, detail, or spatial layout. These points are elaborated in this chapter. We begin with an introduction to the basic theory of color vision to provide a foundation for the applications. The latter half of the chapter consists of a set of four visualization problems requiring the effective use of color; these have to do with color selection interfaces, color labeling, pseudocolor sequences for mapping, color reproduction, and color for multidimensional discrete data. Each has its own special set of requirements. Some readers may wish to skip directly to the applications, sampling the more technical introduction only as needed.

Trichromacy Theory

The most important fact about color vision is that we have three distinct color receptors, called *cones*, in our retinas that are active at normal light levels—hence *trichromacy*. We also have rods, sensitive at low light levels, but they are so overstimulated in all but the dimmest light that their influence on color perception can be ignored. Thus, in order to understand color vision, we need only consider the cones. The fact that there are only three receptors is the reason for the basic three-dimensionality of human color vision. The term *color space* means an arrangement of colors in a three-dimensional space. In this chapter, a number of color spaces, designed for different purposes, are discussed. Complex transformations are sometimes required to convert from one color space to another, but they are all three dimensional, and this three-dimensionality derives ultimately from the three cone types. This is the reason why there are three different colors of liquid crystal in a television screen—red, green, and blue—and this is the reason why we learn in school that there are three primary paint colors—red, yellow, and blue. It is also the reason why printers have a minimum of three colored inks for color printing—cyan, magenta, and yellow. Engineers should be grateful that humans have only three color receptors. Some birds, such as chickens, have as many as 12 different kinds of color-sensitive cells. A television set for chickens would require 12 types of differently colored pixels!

Figure 4.2 shows the human cone sensitivity functions. The plots show how light of different wavelengths is absorbed by the three different receptor types (S, M, L). It is evident that two of the functions, L and M, which peak at 540 nanometers and 580 nanometers, respectively, overlap considerably; the third, S, is much more distinct, with peak sensitivity at 450 nanometers. The short-wavelength S receptor absorbs light in the blue part of the spectrum and is much less sensitive, which is another reason (besides chromatic aberration, discussed in Chapter 2) why we should not show detailed information such as text in pure blue on a black background.

Because only three different receptor types are involved in color vision, it is possible to match a particular patch of colored light with a mixture of just three colored lights, usually called *primaries*. It does not matter that the target patch may have a completely different spectral composition. The only thing that matters is that the matching primaries are balanced to produce the same response from the cone receptors as the

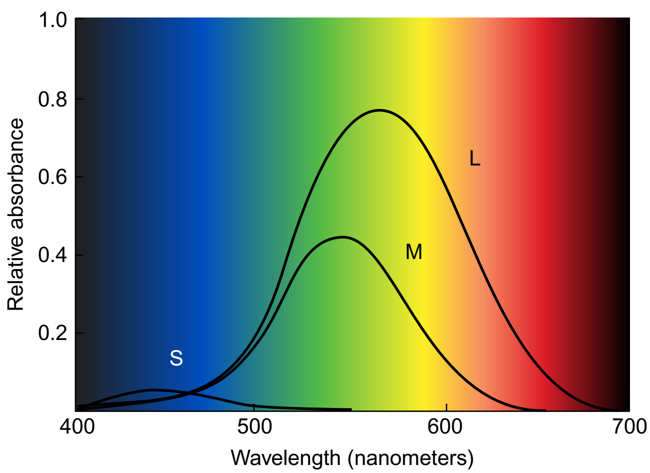

Figure 4.2 Cone sensitivity functions. The colors are only rough approximations to spectrum hues. *Abbreviations*: S, short-wavelength cone sensitivity; M, medium-wavelength cone sensitivity; L, long-wavelength cone sensitivity.

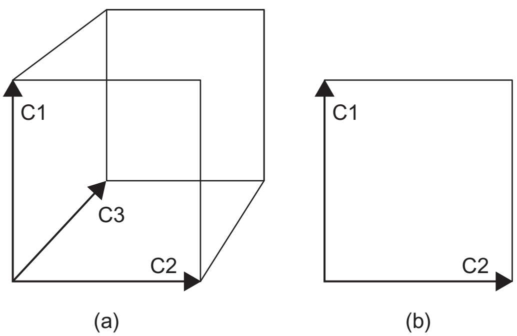

Figure 4.3 (a) Cone response space defined by the response to a colored light of each of the three cone types. (b) The space becomes two dimensional in the case of common color deficiencies.

patch of light to be matched. Figure 4.3(a) illustrates the three-dimensional space formed by the responses of the three cones.

Color Blindness

An unfortunate result of using color for information coding is the creation of a new class of people with a disability. Color blindness already disqualifies applicants for some jobs, such as telephone line maintenance workers, because of the myriad colored wires, and pilots, because of the need to distinguish color-coded lights. About 10% of the male population and about 1% of the female population have some form of color vision deficiency. The most common deficiencies are explained by lack of either the long-wavelength-sensitive cones (protanopia) or the medium-wavelength-sensitive cones (deuteranopia). Both protanopia and deuteranopia result in an inability to distinguish red and green, meaning that the cherries in Figure 4.1 are difficult for people with these deficiencies to see. One way to describe color vision deficiency is by pointing out that the three-dimensional color space of normal color vision collapses to a two-dimensional space, as shown in Figure 4.3(b).

Color Measurement

The fact that we can match any color with a mixture of no more than three primary lights is the basis of colorimetry. An understanding of colorimetry is essential for anyone who wishes to specify colors precisely for reproduction.

We can describe a color by the following equation:

$$C \equiv rR + gG + bB \tag{4.1}$$

where C is the color to be matched; R, G, and B are the primary light sources to be used to create a match; and r, g, and b represent the amounts of each primary light. The $\equiv$ symbol is used to denote a perceptual match; that is, the sample and the mixture of the red, green, and blue (rR, gG, bB) primaries look identical. Figure 4.4 illustrates the concept. Three projectors are set up with overlapping beams. In the figure, the beams only partially overlap so that the mixing effect can be illustrated, but in a color-matching experiment they would overlap perfectly. To match the lilac-colored sample, the projectors are adjusted so that a large amount of light comes from the red and blue projectors and a smaller amount of light comes from the green projector.

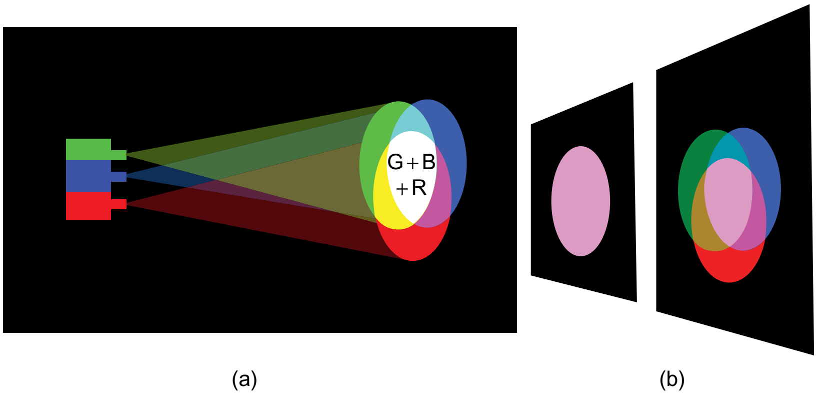

Figure 4.4 A color-matching setup. (a) When the light from three projectors is combined the results are as shown. Yellow light is a mixture of red and green. Purple light is a mixture of red and blue. Cyan light is a mixture of blue and green. White light is a mixture of red, green, and blue. (b) Any other color can be matched by adjusting the proportions of red, green, and blue lights.

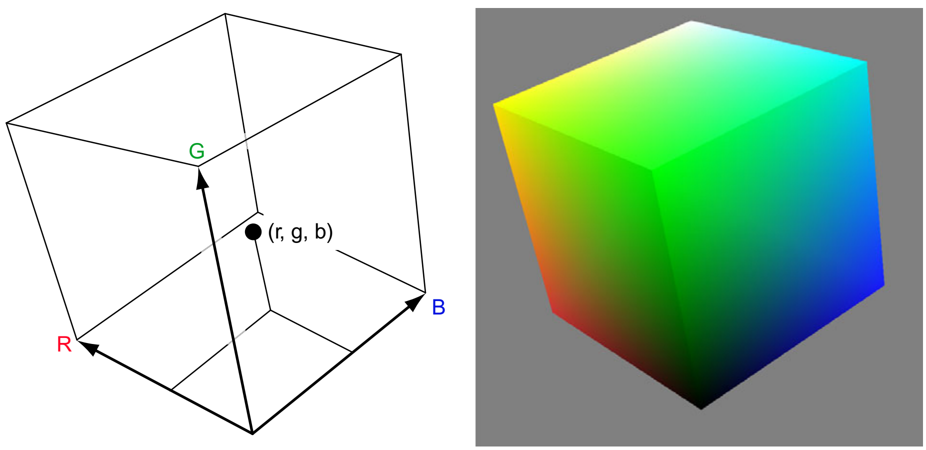

Figure 4.5 The three-dimensional space formed by three primary lights. Any internal color can be created by varying the amount of light produced by each of the primaries.

The *RGB* primaries form the coordinates of a color space, as illustrated in Figure 4.5. If these primaries are physically formed by the phosphor colors of a color monitor, this space defines the *gamut* of the monitor. In general, a gamut is the set of all colors that can be produced by a device or sensed by a receptor system.

It seems obvious that restrictions must be placed on this formulation. So far, we have assumed that the primaries are red, green, and blue, but what if we were to choose other primary lights—for example, yellow, blue, and purple? We have stated no rule saying they must be red, green, and blue. How could we possibly reproduce a patch of red light out of combinations of yellow, blue, and purple lights? In fact, we can only reproduce colors that lie within the *gamut* of the three primaries. Yellow, blue, and purple would simply have a smaller gamut, meaning that if we used them then a smaller range of colors could be reproduced.

The relationship defined in Equation 4.1 is a linear relationship; consequently, if we double the amount of light on the left, we can double the amount of light on each of our primaries and the match will still hold. To make the math simpler, it is also useful to allow the concept of negative light. Thus, we may allow expressions such as

$$C \equiv -rR + gG + bB \tag{4.2}$$

Although this concept may seem nonsensical, because negative light does not exist in nature, it is, in fact, practically useful in the following situation. Suppose we have a colored light that cannot be matched because it is outside the gamut of our three primary sources. We can still achieve a match by adding part of one of the primaries to our sample. If the test samples and the *RGB* primaries are all projected as shown in Figure 4.4, this can be achieved by swiveling one of the projectors around and adding its light to the light of the sample.

If the red projector were redirected in this way, we would have

$$C + rR \equiv gG + bB \tag{4.3}$$

which can be rewritten as

$$C \equiv -rR + gG + bB \tag{4.4}$$

Once we allow the concept of negative values for the primaries, it becomes possible to state that any colored light can be matched by a weighted sum of *any* three primaries as long as each is distinctive in cone space. The primaries do not even have to match an actual color, and in fact the most widely used color standard is based on non-physical primaries, as we shall see.

Change of Primaries

Primaries are arbitrary from the point of view of color mixture—there is no special red, green, or blue light that must be used. Fundamental to colorimetry is the ability to change from one set of primaries to another. This gives us freedom to choose any set of primaries we want. We can choose as primaries the liquid crystal hues of a monitor, three differently colored lasers, or some hypothetical set of lamps. We can even choose to base our primaries on the sensitivities of the human cone receptors. Given a standard way of specifying colors (using a standard set of primaries), we can use a transformation to create that same color on any number of different output devices. This transformation is described in Appendix A.

We now have the foundations of a color measurement and specification system. To illustrate how color specification works, it is useful to think about how it might be done with real lamps, before moving toward more abstract concepts. Red, green, and blue lamps could be manufactured to precise specifications and set up in an instrument so that the amounts of red, green, and blue light falling on a standard white surface could be set by adjusting three calibrated dials, one for each lamp. Identical instruments, each containing sets of colored lamps, would be sent around the world to color experts. Then, to give a precise color specification to someone with the standard instrument, we would simply need to make a color match by adjusting the dials and sending that person the dial settings. The recipient could then adjust his or her own standard lamps to reproduce the color.

Of course, although this approach is theoretically sound, it is not very practical. Standard primary lamps would be very difficult to maintain and calibrate and they would be very expensive. But, we can apply the principle by creating a set of *abstract* primary lamps defined on the basis of the human receptor characteristics. This is how color specification systems work.

One of the basic concepts in any color standard is that of the standard observer. This is a hypothetical person whose color sensitivity functions are held to be typical of all humans. The idea assumes that everyone has the same receptor functions. In fact, although humans do not display exactly the same sensitivities to different colors, with the exception of the color deficiencies, they come close. Most serious color specification is done using the *Commission Internationale de l'Eclairage* (CIE) system of color standards. These are based on standard observer measurements that were made prior to 1931. Color measuring instruments contain glass filters that are derived from the specifications of the human standard observer. One advantage is that glass filters are more stable than lamps.

The CIE system uses a set of abstract observer sensitivity functions called *tristimulus values*; these can be thought of as a set of abstract receptors and they are labeled XYZ. They are transformations of actual measured sensitivities, chosen for their mathematical properties. One important feature of the system is that the Y tristimulus value is the same as luminance. More details of the way the system is derived are given in Appendix B.

Figure 4.6 illustrates the color volume created by the XYZ tristimulus functions of the CIE system. The colors that can actually be perceived are represented as a gray volume entirely contained within the positive space defined by the axes. The colors that can be created by a set of three colored lights, such as the red, green, and blue

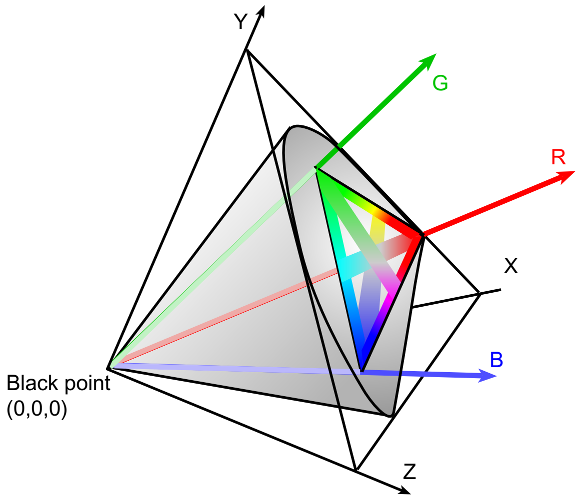

Figure 4.6 The *X*, *Y*, and *Z* axes represent the CIE standard virtual primaries. Within the positive space defined by the axes, the gamut of perceivable colors is represented as a gray solid. The colors that can be created by means of the red, green, and blue monitor primaries are defined by the pyramid enclosed by the *R*, *G*, and *B* lines.

monitor phosphors, are defined by the pyramid-shaped volume within the *RGB* axes, as shown. This is the *monitor gamut*. The *X*, *Y*, and *Z* axes are the CIE primaries, and they are outside the gamut of physically realizable colors.

The CIE tristimulus system based on the standard observer is by far the most widely used standard for measuring colored light. For this reason, it should always be used when precise color specification is required. Because a monitor is a light-emitting device with three primaries, it is relatively straightforward to calibrate a monitor in terms of the CIE coordinates. If a color generated on one monitor, such as a cathode ray tube (CRT), is to be reproduced on another, such as a liquid crystal display, the best procedure is first to convert the colors into the CIE tristimulus values and then to convert them into the primary space of the second monitor.

The specification of surface colors is far more difficult than the specification of lights, because an illuminant must be taken into account and because, unlike lights, pigment colors are not additive. The color that results from mixing paints is difficult to predict because of the complex way that light interacts with pigment. A treatment of surface color measurement is beyond the scope of this book, although later we will deal with perceptual issues related to color reproduction.

Chromaticity Coordinates

The three-dimensional abstract space represented by the *XYZ* coordinates is useful for specifying colors, but it is difficult to understand. As discussed in Chapter 3, there are good reasons for treating lightness, or luminance, information as special. In everyday speech, we often refer to the color of something and its lightness as different and independent properties. Thus, it is useful to have a measure that defines the hue and vividness of a color while ignoring the amount of light. *Chromaticity coordinates* have exactly this property through normalizing with respect to the amount of light.

To transform tristimulus values to chromaticity coordinates, use

$$\begin{aligned} x &= X/(X+Y+Z) \\ y &= Y/(X+Y+Z) \\ z &= Z/(X+Y+Z) \end{aligned} \tag{4.5}$$

Because $x + y + z = 1$, it is sufficient to use x, y values only. It is common to specify a color by its luminance (Y) and its x, y chromaticity coordinates (x, y, Y). The inverse transformation from x, y, Y to tristimulus values is

$$\begin{aligned} X &= Yx/y \\ Y &= Y \\ Z &= (1-x-y)Y/y \end{aligned} \tag{4.6}$$

Figure 4.7 shows a CIE x, y chromaticity diagram and graphically illustrates some of the colorimetric concepts associated with it. Some of the useful and interesting properties of the chromaticity diagram include the following:

1. If two colored lights are represented by two points in a chromaticity diagram, the color of a mixture of those two lights will always lie on a straight line between those two points.

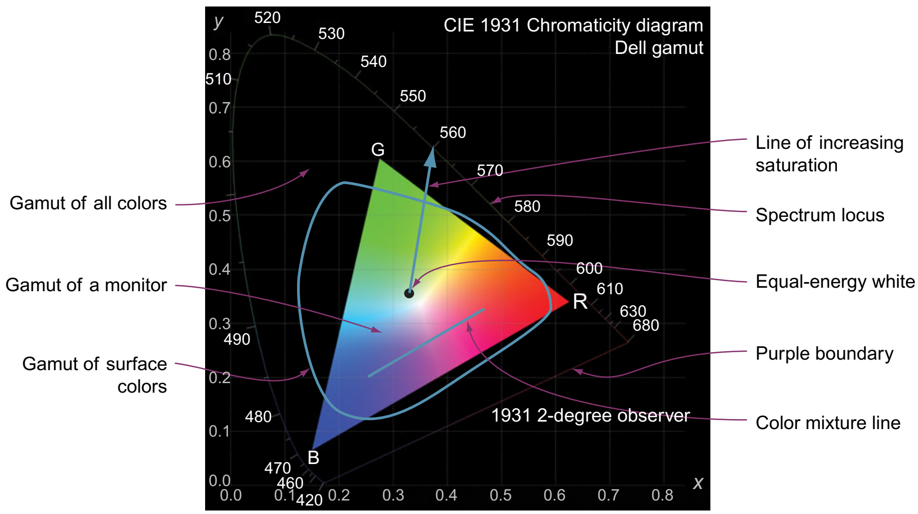

Figure 4.7 CIE chromaticity diagram with various interesting features added. The colored triangle represents the gamut of a computer monitor. Colors as shown are only approximate.

2. Any set of three lights specifies a triangle in the chromaticity diagram. Its corners are given by the chromaticity coordinates of the three lights. Any color within that triangle can be created with a suitable mixture of the three lights. Figure 4.7 illustrates this with typical monitor *RGB* primaries.

3. The *spectrum locus* is the set of chromaticity coordinates of pure monochromatic (single-wavelength) lights. All realizable colors fall within the spectrum locus.

4. The *purple boundary* is the straight line connecting the chromaticity coordinates of the longest visible wavelength of red light (about 700 nm) to the chromaticity coordinates of the shortest visible wavelength of blue (about 400 nm).

5. The chromaticity coordinates of equal-energy white (light having an equal mixture of all wavelengths) are 0.333, 0.333. But, when a white light is specified for some application, what is generally required is one of the CIE standard illuminants. The CIE specifies a number that corresponds to different phases of daylight; of these, the most commonly used is D65. D65 was made to be a careful approximation of daylight with an overcast sky. It also happens to be very close to the mix of light that results when both direct sunlight and light from the rest of the sky fall on a horizontal surface. D65 also corresponds to a black-body radiator at 6500 degrees Kelvin. D65 has chromaticity coordinates $x = 0.313$, $y = 0.329$. Another CIE standard illuminant corresponds to the light produced by a typical incandescent tungsten source. This is illuminant A (chromaticity coordinates $x = 0.448$, $y = 0.407$), and it is considerably more yellow than normal daylight.

6. *Excitation purity* is a measure of the distance along a line between a particular pure spectral wavelength and the white point. Specifically, it is the value given by dividing the distance between the sample and the white point by the distance between the white point and the spectrum locus (or purple boundary). This measure defines the vividness of a color. A less technical, but commonly used, term for this quantity is *saturation*. More saturated colors are more vivid.

7. The complementary wavelength of a color is produced by drawing a line between that color and white and extrapolating to the opposite spectrum locus. Adding a color and its complementary color produces white.

There is a widely used standard for the color of monitor primaries called *sRGB*. The chromaticity coordinates for sRGB are set out in Table 4.1.

When a computer display is used to generate a color, the CIE tristimulus values formed from some set of red, green, and blue settings can be calculated by the following formula:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} \dfrac{x_R}{y_R} & \dfrac{x_G}{y_G} & \dfrac{x_B}{y_B} \\ 1 & 1 & 1 \\ \dfrac{z_R}{y_R} & \dfrac{z_G}{y_G} & \dfrac{z_B}{y_B} \end{bmatrix} \begin{bmatrix} Y_R \\ Y_G \\ Y_B \end{bmatrix} \tag{4.7}$$

Table 4.1 *Cromaticity Coordinates for the sRGB Standard*

	Red	Green	Blue
x	0.64	0.30	0.15
y	0.33	0.60	0.06

where (x_R, y_R, z_R), (x_G, y_G, z_G), and (x_B, y_B, z_B) are the chromaticity coordinates of the particular monitor primaries, and Y_R, Y_G, and Y_B are the actual luminance values produced from each phosphor for the particular color being converted. Notice that for a particular monitor the transformation matrix will be constant; only the Y vector will change.

To generate a particular color on a monitor that has been defined by CIE tristimulus values, it is only necessary to invert the matrix and create an appropriate voltage to each of the red, green, and blue electron guns of the monitor. Naturally, to determine the actual value that must be specified, it is necessary to calibrate the monitor's red, green, and blue outputs in terms of luminance and apply gamma correction, as described in Chapter 3. Once this is done, the monitor can be treated as a linear color creation device with a particular set of primaries, depending on its phosphors. For more on monitor calibration, see Cowan (1983). It is also possible to purchase self-calibrating monitors adequate for all but the most demanding applications.

Color Differences and Uniform Color Spaces

Sometimes it is useful to have a color space in which equal perceptual distances are equal distances in the space. Here are three applications:

- **Specification of color tolerances.** When a manufacturer wishes to order a colored part from a supplier, such as a plastic molding for an automobile, it is necessary to specify the color tolerance within which the part will be accepted. It only makes sense for this tolerance to be based on human perception, because ultimately it is people who decide whether the door trim matches the upholstery.
- **Specification of color codes.** If we need a set of colors to code data, such as different wires in a cable, we would normally like those colors to be as distinct as possible so that they will not be confused. This can be accomplished by making them as far apart as possible in a uniform color space.
- **Pseudocolor sequences for maps.** Many scientific maps use sequences of colors to represent ordered data values. This technique, called *pseudocoloring*, is widely used in astronomy, physics, medical imaging, and geophysics. A uniform color space can be used to create perceptually equal steps in a sequence of colors.

The CIE XYZ color space is very far from being perceptually uniform; however, in 1978, the CIE produced a set of recommendations on the use of two uniform color spaces that are transformations of the *XYZ* color space. These are called the *CIElab* and the *CIEluv* uniform color spaces. The reason why there are two color spaces, rather than one, has to do with the fact that different industries, such as the paint industry, had already adopted one standard or the other. Also, the two standards have somewhat different properties that make them useful for different tasks. Only the *CIEluv* formula is described here. It is generally held to be better for specifying large color differences; however, one measurement made using the *CIElab* color difference formula is worth noting. Using *CIElab*, Hill et al. (1997) estimated that there are between two and six million discriminable colors available within the gamut of a color monitor.

The *CIEluv* equations are:

$$\begin{aligned} L^* &= 116(Y/Y_n)^{1/3} - 16 \\ u^* &= 13L^*(u' - u'_n) \\ v^* &= 13L^*(v' - v'_n) \end{aligned} \tag{4.8}$$

where

$$\begin{aligned} u' &= \frac{4X}{X + 15Y + 3Z} \quad & u'_n &= \frac{4X}{X_n + 15Y_n + 3Z_n} \\ v' &= \frac{9Y}{X + 15Y + 3Z} \quad & v'_n &= \frac{4X}{X_n + 15Y_n + 3Z_n} \end{aligned} \tag{4.9}$$

u' and v' are a projective transformation of the x, y chromaticity diagram, designed to produce a perceptually more uniform color space. X_n, Y_n, and Z_n are the tristimulus values of a reference white. To measure the difference between colors, ΔE^*_{uv}, the following formula is used:

$$\Delta E^*_{uv} = \sqrt{(\Delta L^*)^2 + (\Delta u^*)^2 + (\Delta v^*)^2} \tag{4.10}$$

The *CIEluv* system retains many of the useful properties of the *XYZ* tristimulus values and the x, y chromaticity coordinates.

The u', v' diagram is shown in Figure 4.8. Its official name is the *CIE 1976 Uniform Chromaticity Scale diagram*, or UCS diagram. Because u', v' is a projective transformation, it retains the useful property that blends of two colors will lie on a line between the u', v' chromaticity coordinates. (It is worth noting that this is not a property of the *CIElab* uniform color space.)

The u^*, v^* values change the scale of u', v' with respect to the distance from black to white defined by the sample lightness, L^* (recall from Chapter 3 that L^* requires Y_n, a reference white in the application environment). The reason for this is straightforward: The darker the colors, the fewer we can see. At the limit, there is only one color: black.

A value of 1 for ΔE^*_{uv} is an approximation to a *just noticeable difference* (JND).

Although they are useful, uniform color spaces provide, at best, only a rough first approximation of how color differences will be perceived. In complex environments, many factors influence how much difference is seen between two adjacent colors. Contrast effects can radically alter the shape of the color space. Small patches of light give different results than large patches. In general, we are much more sensitive to differences between large patches of color. When the patches are small, the perceived differences are smaller, and this is especially true in the yellow–blue direction. Ultimately, with very small samples, small-field tritanopia occurs; this is the inability to distinguish colors that are different in the yellow–blue direction. Figure 4.9 shows two examples of large patches of color on a white background

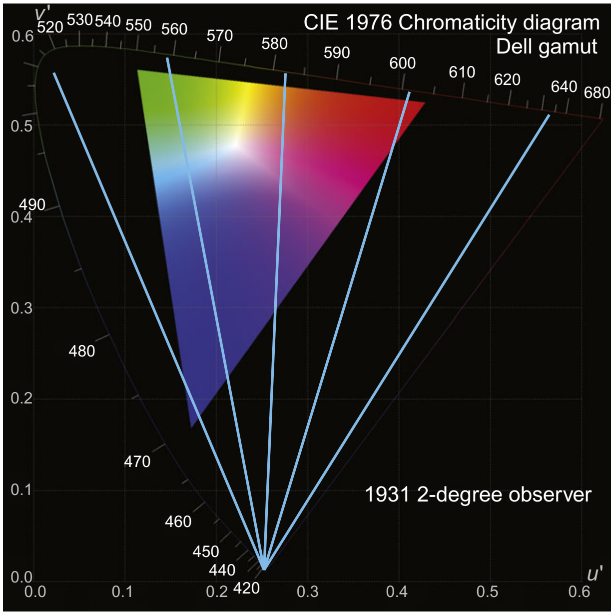

Figure 4.8 CIE $Lu'v'$ UCS diagram. The lines radiating from the lower part of the diagram are called *tritanopic confusion lines*. Colors that differ along these lines can still be distinguished by the great majority of color-blind individuals.

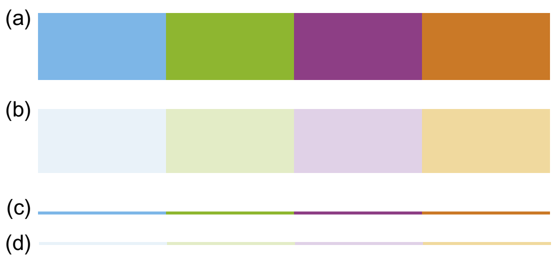

Figure 4.9 (a) Large samples of saturated colors. (b) Large samples of the same colors less saturated. (c) Small samples of the same saturated colors. (d) Small samples of the less saturated colors.

and the same set of colors in smaller patches. In the larger patches, the low-saturation colors are easy to distinguish. They are not so easy to distinguish in the small patches.

[G4.1] Use more saturated colors when color coding small symbols, thin lines, or other small areas. Use less saturated colors for coding large areas.

Opponent Process Theory

Late in the 19th century, German psychologist Ewald Hering proposed the theory that there are six elementary colors and that these colors are arranged perceptually as opponent pairs along three axes: black–white, red–green, and yellow–blue (Hering, 1920). In recent years, this principle has become a cornerstone of modern color theory, supported by a variety of experimental evidence (for a review, see Hurvich, 1981). Modern opponent process theory has a well-established physiological basis: Input from the cones is processed into three distinct channels immediately after the receptors. The luminance channel (black–white) is based on input from all the cones. The red–green channel is based on the difference of long- and middle-wavelength cone signals. The yellow–blue channel is based on the difference between the short-wavelength cones and the sum of the other two. These basic connections are illustrated in Figure 4.10. There are many lines of scientific evidence for the opponent process theory. These are worth examining, because they provide useful insights.

Naming

Opponent color theory predicts that certain color names should not occur in combination. We often describe colors using combinations of color terms, such as *yellowish green* or *greenish blue*. The theory predicts that people will never use *reddish green* or

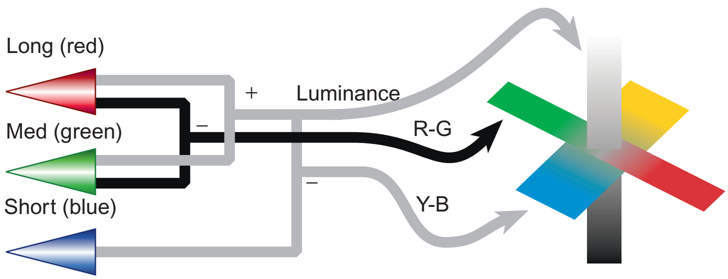

Figure 4.10 In the color opponent process model, cone signals are transformed into black–white (luminance), red–green, and yellow–blue channels.

yellowish blue, because these colors are polar opposites in the opponent color theory (Hurvich, 1981). Experiments have confirmed this.

Cross-Cultural Naming

In a remarkable study of more than 100 languages from many diverse cultures, anthropologists Berlin and Kay (1969) showed that primary color terms are remarkably consistent across cultures (Figure 4.11). In languages with only two basic color words, these are always black and white; if a third color is present, it is always red; the fourth and fifth are either yellow and then green, or green and then yellow; the sixth is always blue; the seventh is brown, followed by pink, purple, orange, and gray in no particular order. The key point here is that the first six terms define the primary axes of an opponent color model. This provides strong evidence that the neural basis for these names is innate; otherwise, we might expect to find cultures where lime green or turquoise is a basic color term. The cross-cultural evidence strongly supports the idea that certain colors—specifically, red, green, yellow, and blue—are far more valuable in coding data than others.

Unique Hues

There is something special about yellow. If subjects are given control over a device that changes the spectral hue of a patch of light and are told to adjust it until the result is a pure yellow, neither reddish nor greenish, they do so with remarkable accuracy. In fact, they are typically accurate within 2 nm (Hurvich, 1981).

Interestingly, there is good evidence for two unique greens. Most people set a pure green at about 514 nm, but about a third of the population sees pure green at about 525 nm (Richards, 1967). This may be why some people argue about the color turquoise; some people consider it to be a variety of green, whereas others consider it to be a kind of blue.

It is also significant that unique hues do not change a great deal when the overall luminance level is changed (Hurvich, 1981). This supports the idea that chromatic perception and luminance perception really are independent.

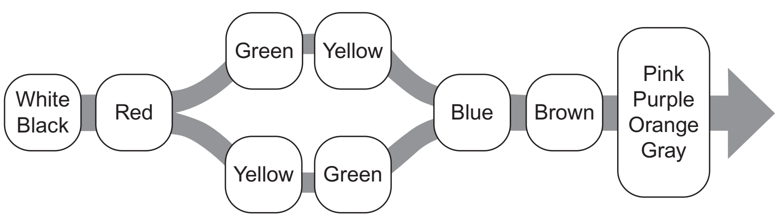

Figure 4.11 This is the order of appearance of color names in languages around the world, according to the research of Berlin and Kay (1969). The order is fixed, with the exception that sometimes yellow is present before green and sometimes the reverse is the case.

Neurophysiology

Neurophysiological studies have isolated classes of cells in the primary visual cortexes of monkeys that have exactly the properties of opponency required by the opponent process theory. Red–green and yellow–blue opponent cells exist, and other configurations do not appear to exist (de Valois & de Valois, 1975).

Categorical Colors

There is evidence that certain colors are canonical in a sense that is analogous to the philosopher Plato's theory of forms. Plato proposed that there are ideal objects, such as an ideal horse or an ideal chair, and that real horses and chairs can be defined in terms of their differences from the ideal. Something like this appears to operate in color naming. If a color is close to an ideal red or an ideal green, it is easier to remember. Colors that are not basic, such as orange or lime green, are not as easy to remember.

There is evidence that confusion between color codes is affected by color categories. Kawai et al. (1995) asked subjects to identify the presence or absence of a chip of a particular color. The subjects took much longer if the chip was surrounded by distracting elements that were of a different color but belonged to the same color category than if the chip was surrounded by distracting elements that were equally distinct according to the sense of a uniform color space but crossed a color category boundary.

Post and Greene (1986) carried out an extensive experiment on the naming of colors produced on a computer monitor and shown in a darkened room. They generated 210 different colors, each in a 2-degree (of visual angle) patch with a black surround. Perceiving colors in darkness and in isolation is a very special case that is very different from the usual way we see color, so the results should not be taken as generally applicable. Nevertheless they are interesting.

Figure 4.12 illustrates the color areas that were given a specific name with at least 75% reliability. A number of points are worth noting:

- The fact that only eight colors plus white were consistently named, even under these highly standardized conditions, strongly suggests that only a very small number of colors can be used effectively as category labels.
- The pure monitor red was actually named orange most of the time. A true color red required the addition of a small amount from the blue monitor primary.
- The specific regions of color space occupied by particular colors should not be given much weight. The data was obtained with a black background. Because of contrast effects, different results are to be expected with white and colored backgrounds.

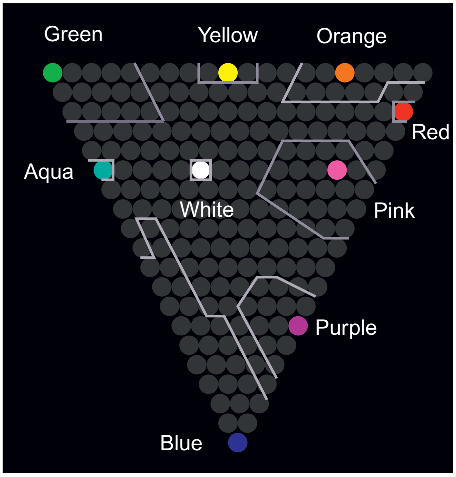

Figure 4.12 The results of an experiment in which subjects were asked to name 210 colors produced on a computer monitor. Outlined regions show the colors that were given the same name with better than 75% probability.

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Properties of Color Channels

From the perspective of data visualization, the different properties of the color channels have profound implications for the use of color. The most significant differences are between the two chromatic channels and the luminance channel, although the two color channels also differ from each other.

To display data on the luminance channel *alone* is easy; it is stimulated by patterns that vary only from black to white through shades of gray. But, with careful calibration (which must be customized to individual subjects), patterns can be constructed that vary only for the red–green or the yellow–blue channel. A key quality of such a pattern is that its component colors must not differ in luminance. This is called an *isoluminant* or *equiluminous* pattern. In this way, the different properties of the color channels can be explored and compared with the luminance channel capacity.

Spatial Sensitivity

According to a study by Mullen (1985), the red–green and yellow–blue chromatic channels are each capable of carrying only about one-third the amount of detail carried by the black–white channel. Because of this, purely chromatic differences are not suitable for displaying any kind of fine detail. Figure 4.13 illustrates this problem with colored text on an equiluminous background. In the part of the figure where there is only a chromatic difference between the text and the background, the text becomes very difficult to read.

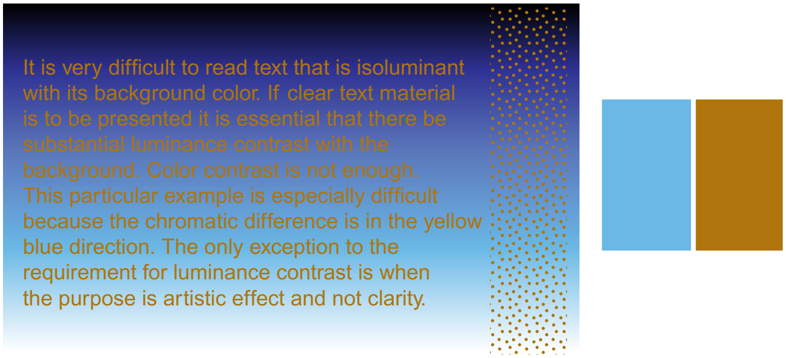

Figure 4.13 Brown text on a blue gradient. Notice how difficult it is to read the text where the luminance is equal, despite a large chromatic difference. Brown is a dark yellow so these colors differ on the blue–yellow channel.

[G4.2] When small symbols, text, or other detailed graphical representations of information are displayed using color on a differently colored background, always ensure luminance contrast with the background. This guideline is a variation of G3.4.

Stereoscopic Depth

It appears to be impossible, or at least very difficult, to see stereoscopic depth in stereo pairs that differ only in terms of the color channels (Lu & Fender, 1972; Gregory, 1977). This is because stereoscopic depth perception is based primarily on information from the luminance channel.

[G4.3] Ensure adequate luminance contrast in order to define features important for perceiving stereoscopic depth.

Motion Sensitivity

If a pattern is created that is equiluminous with its background and contains only chromatic differences, and that pattern is set in motion, something strange occurs. The moving pattern appears to move much more slowly than a black against white pattern moving at the same speed (Anstis & Cavanaugh, 1983). Motion perception appears to be primarily based on information from the luminance channel.

[G4.4] Ensure adequate luminance contrast in order to define features important for perceiving moving targets.

Form

We are very good at perceiving the shapes of surfaces based on their shading; however, when the shading is transformed from a luminance gradient into a purely chromatic gradient, the impression of surface shape is much reduced. Perception of shape and form appears to be processed mainly through the luminance channel (Gregory, 1977).

> **[G4.5]** When applying shading to define the shape of a curved surface, use adequate luminance (as opposed to chromatic) variation. This is a supplement to G2.1.

Even though small shapes should not be defined by purely chromatic boundaries, this does not apply to large shapes, such as the R in Figure 4.14, which can be seen clearly. Nevertheless, the shape will be more clearly perceived if a luminance difference border is added, however thin. This also helps distinguish the color of the shape.

> **[G4.6]** If large areas are defined using nearly equiluminous colors, consider using thin border lines with large luminance differences (from the colors of the areas) to help define the shapes.

To summarize this set of properties, the red–green and yellow–blue channels are inferior to the luminance channel in almost every respect. The implications for data display are clear. Purely chromatic differences should never be used for displaying object shape, object motion, or detailed information such as text. From this perspective, color would seem almost irrelevant and certainly a secondary method for information display; nevertheless, when it comes to coding information, using color to display data categories is usually the best choice. To see why, we need to look beyond the basic processes that we have been considering thus far.

Figure 4.14 Even large shapes are seen more clearly if a luminance contrast boundary is provided.

Color Appearance

Color (as opposed to luminance) processing, it would appear, does not help us to understand the shape and layout of objects in the environment. Color does not help the hunter aim an arrow accurately. Color does not help us see shape from shading and thereby shape a lump of clay or bread dough. Color does not help us use stereoscopic depth to guide our hands when we reach out to grasp something. But color is useful to the gatherer of food. Fruits and berries are often distinguished by their color.

Color creates a kind of visual attribute of objects: This is a red berry; that is a yellow door. Color names are used as adjectives because colors are perceived as attributes of objects. This suggests a most important role for color in visualization—namely, the coding of information. Visual objects can represent complex data entities, and colors can naturally code attributes of those objects.

Monitor Surrounds

The XYZ tristimulus values of a patch of light physically define a color, but they do not tell us how it will appear. Depending on the surrounding colors in the environment and a whole host of spatial and temporal factors, the same physical color can look very different. If it is desirable that color appearance be preserved, it is important to pay close attention to surrounding conditions. In a monitor-based display, a large patch of standardized reference white will help ensure that color appearance is preserved. When colors are reproduced on paper, viewing them under a standard lamp will help preserve their appearance. In the paint and fabric industries, where color appearance is critical, standard viewing booths are used. These booths contain standard illumination systems that can be set to approximate daylight or a standard indoor illuminant, such as a typical tungsten lightbulb or halogen lamp.

Color Constancy

The mechanisms of surface lightness constancy, discussed at some length in Chapter 3, generalize to trichromatic color perception. Both chromatic adaptation and chromatic contrast occur and play a role in color constancy. Differential adaptation in the cone receptors helps us to discount the color of the illumination in the environment. When there is colored illumination, different classes of cone receptors undergo independent changes in sensitivity; thus, when the illumination contains a lot of blue light, the short-wavelength cones become relatively less sensitive than the others. The effect of this is to shift the neutral point at which the three receptor types are in equilibrium, such that more blue light must be reflected from a surface for it to seem white. This discounting of the illumination, of course, is exactly what is necessary for color constancy. A piece of everyday evidence that adaptation is effective is the fact that not many people are aware of how much yellower ordinary tungsten room lighting is than daylight. The consequence for adaptation is that we cannot see absolute colors, and when colored symbols appear on differently colored backgrounds their apparent hue will be altered.

Color Contrast

Chromatic contrast occurs in a way that is similar to the lightness contrast effects discussed and illustrated in Chapter 3. Figure 4.15 shows a color contrast illusion. It has been shown that contrast effects can distort readings from color-coded maps (Cleveland & McGill, 1983; Ware, 1988). Contrast effects can be theoretically accounted for by activity in the color opponent channels (Ware & Cowan, 1982). However, as with lightness contrast, the ultimate purpose of the contrast-causing mechanism is to help us see surface colors accurately by revealing differences between colored patches and background regions.

From the point of view of the monitor engineer and the user of color displays, the fact that colors are perceived relative to their overall context has the happy consequence of making the eye relatively insensitive to poor color balance. Try comparing an image on a computer screen with that same image printed. Individual colors will undoubtedly be very different, but the overall impression and the information conveyed will be mostly preserved. This is because relative color is much more important than absolute color.

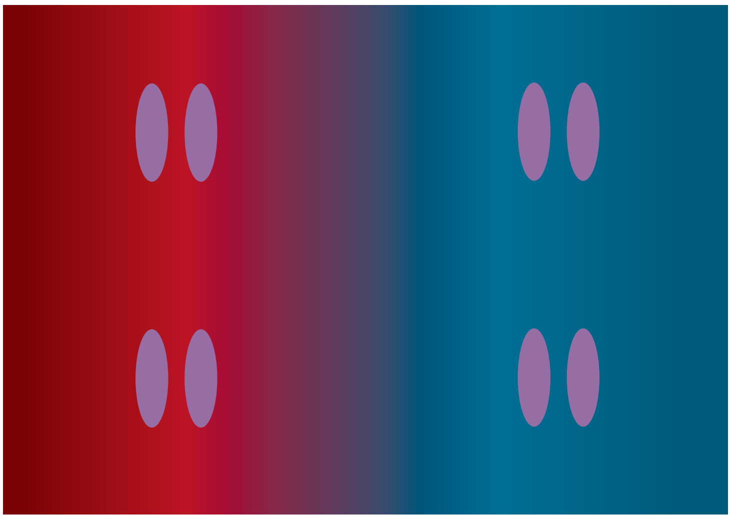

Figure 4.15 A color contrast illusion. The ellipses are all the same color but seem pinker on the right and bluer on the left.

Saturation

When describing color appearance in everyday language, people use many terms in rather imprecise ways. Besides using color names such as *lime green*, *mauve*, *brown*, *baby blue*, and so on, people also use adjectives such as *vivid*, *bright*, and *intense* to describe colors that seem especially pure. Because these terms are used so variably, scientists use the technical term *saturation* to denote how pure colors seem to the viewer. A high-saturation color is vivid, and a low-saturation color is close to black, white, or gray. In terms of the color opponent channels, high-saturation colors are those that give a strong signal on one or both of the red–green and yellow–blue channels.

Equal-saturation contours have been derived from psychophysical experiments (Wyszecki & Stiles, 1982). Figure 4.16(a) shows a plot of equal-saturation values in a CIE chromaticity diagram. These contours, derived from studies of human perception, show that it is possible to obtain much more highly saturated red, green, and blue colors on a monitor than yellow, cyan, or purple values. Figure 4.16(b) shows equal-saturations contours (not derived from perception) in the popular hue, saturation, and value (HSV) transformation commonly used in computer graphics (Smith, 1978). Comparing the two diagrams, it is striking that two colors having equal HSV saturations will not have close to equal perceptual saturation. In particular, pure red, green, and blue on a monitor will be more perceptually saturated than pure cyan, magenta, or yellow. To obtain a set of perceptually equally saturated colors we would have to restrict our color gamut to contour 6 in Figure 4.15(a), but this would mean giving up a large amount of useful RGB color space, including the most vivid colors, so this is usually inadvisable.

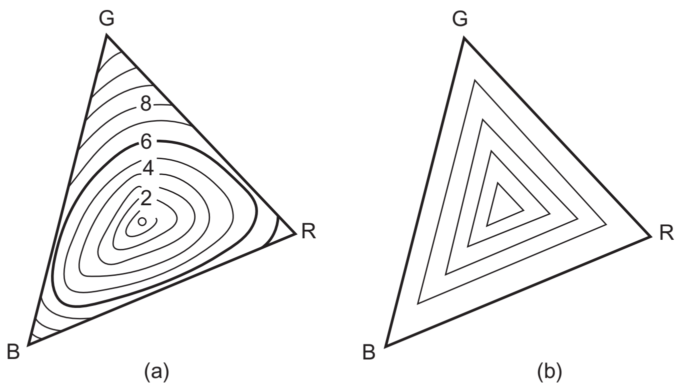

Figure 4.16 (a) The triangle represents the gamut of colors obtained using a computer monitor plotted in CIE chromaticity coordinates. The contours show perceptually determined equal-saturation contours. (b) Equal-saturation contours created using the HSV color space, also plotted in chromaticity coordinates.

Using the general principle that stronger visual effects should be used to show greater quantities (G1.3), we can establish a guideline for the use of saturation in color coding. Because there are few discriminable steps in saturation, and because of contrast effect that may occur if the background is variable, only a few saturation levels can be reliably judged.

> **[G4.7]** If using color saturation to encode numerical quantity, use greater saturation to represent greater numerical quantities. Avoid using a saturation sequence to encode more than three values.

Brown

Brown is one of the most mysterious colors. Brown is dark yellow. Whereas people talk about a light green or a dark green, a light blue or a dark blue, they do not talk about dark yellow. When colors in the vicinity of yellow and orange yellow are darkened, they turn to shades of brown and olive green. Unlike red, blue, and green, brown requires that there be a reference white somewhere in the vicinity for it to be perceived. Brown appears qualitatively different from orange yellow.

There is no such thing as an isolated brown light in a dark room, but when a yellow or yellowish orange is presented with a bright white surround, brown appears. The relevance to visualization is that, if color sets are being devised for the purposes of color coding—for example, a set of blues, a set of reds, a set of greens, and a set of yellows—in the case of yellows, brown may not be recognized as a set member.

Applications of Color in Visualization

So far, this chapter has been mainly a presentation of the basic theory underlying color vision and color measurement. Now we shift the emphasis to applications of color, for which new theory will be introduced only as needed. We will examine four different application areas: color selection interfaces, color labeling, color sequences for map coding, and color reproduction. Each of these presents a different set of problems, and each benefits from an analysis in terms of the human perception of color. We will use these applications to develop guidelines and continue to develop theory.

Application 1: Color Specification Interfaces and Color Spaces

In data visualization software, drawing applications, and CAD systems, it is often essential to let users choose their own colors. There are a number of approaches to this user interface problem. The user can be given a set of controls to specify a point in a three-dimensional color space, a set of color names to choose from, or a palette of predefined color samples.

Color Spaces

The simplest color interface to implement on a computer involves giving someone controls to adjust the amounts of red, green, and blue light that combine to make a patch of color on a monitor. The controls can take the form of sliders, or the user can simply type in three numbers. This provides access, in a straightforward way, to any point within the RGB color cube shown in Figure 4.5; however, although it is simple, many people find this kind of control confusing. For example, most people do not know that to get yellow you must add red and green. There have been many attempts to make color interfaces easier to use.

Many of the most widely used color interfaces in computer graphics are based on the hue, saturation, and value (HSV) color space (Smith, 1978). This is a simple transformation from HSV coordinates to *RGB* monitor coordinates. *Hue*, in Smith's scheme, represents an approximation to the visible spectrum by interpolating in sequence from red to yellow (= red + green) to green to cyan (= green + blue) to blue to purple (= blue + red) and back to red. *Saturation* is the distance from neutral monitor values, on the white–gray–black axis, to the purest hue possible given the limits of monitor primaries. Figure 4.17 shows how hue and saturation can be laid out in two dimensions, with hue on one axis and saturation on the other, based on the HSV transformation of monitor primaries. As Figure 4.16(b) shows, HSV creates only the crudest approximation to perceptually equal saturation contours. *Value* is the name given to the black–white axis. Some color specification interfaces based on HSV allow the user to control hue, saturation, and value variables with three sliders.

Because color research has shown the luminance channel to be very different from the chromatic (red–green, yellow–blue) channels, it is a good idea to separate a luminance

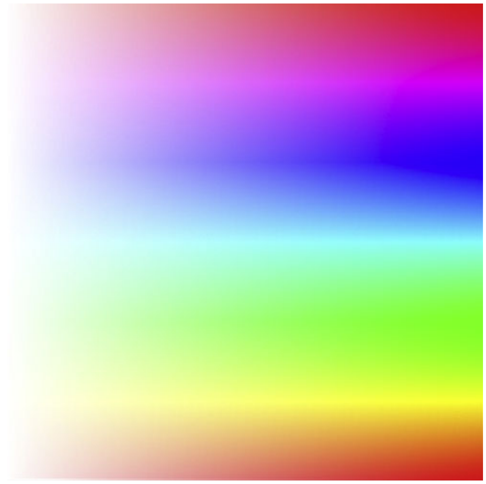

Figure 4.17 This plot shows hue and saturation, based on Smith's (1978) transformation of the monitor primaries.

(or lightness) dimension from the chromatic dimensions in a color specification interface. In addition, because the chromatic channels are perceived integrally, it is usually best to lay out the various hue and saturation choices on a plane, but not as shown in Figure 4.17, as this devotes far too much space to neutral colors and does not reflect the perceptual structure of color space derived from the color opponent channels. Figure 4.18 provides a selection of much better layouts. All are compromises among the constraints of colors produced by computer monitors, the desire to produce a neat geometric space, and the goal of producing a perceptually meaningful representation of a color plane orthogonal to the luminance channel.

> **[G4.8]** In an interface for specifying colors, consider laying out the red–green and yellow–blue channel information on a plane. Use a separate control for specifying the dark–light dimension.

A common interface method is to provide a single slider control for the black–white dimension and to lay out the two opponent color dimensions on a chromatic plane. The idea of laying out colors on a plane has a long history; for example, a color circle is a feature of a color textbook created for artists by Rood (1897). With the invention of computer graphics, it has become far simpler to create and control colors, and many ways of laying out colors are now available.

Figure 4.18(a) shows a color circle with red, green, yellow, and blue defining opposing axes. Many such color circles have been devised over the past century. They differ mainly in the spacing of colors around the periphery.

Figure 4.18(b) shows a color triangle with the monitor primaries, red, green, and blue, at the corners. This color layout is convenient because it has the property that mixtures of two colors will lie on a line between them (assuming proper calibration); however,

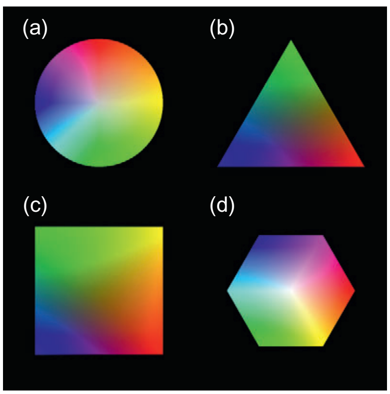

Figure 4.18 A sampling of four different geometric color layouts, each of them embodying the idea of a chromatic plane. (a) Circle. (b) Triangle. (c) Square. (d) Hexagon.

because of linear interpolation, only a very weak yellow occurs between the red and green corners (50% red, 50% green). The strongest yellow on a monitor comes from having both red and yellow at full strength.

Figure 4.18(c) shows a color square with the opponent color primaries, red–green and yellow–blue, at opposite corners (Ware & Cowan, 1990).

Figure 4.18(d) shows a color hexagon with the colors red, yellow, green, cyan, blue, and magenta at the corners. This represents a plane through the single-hexcone color model (Smith, 1978). The hexagon representation has the advantage that it gives both the monitor primaries (red, green, and blue) and the print primaries (cyan, magenta, and yellow) prominent positions around the circumference.

To create a color interface using one of these color planes, it is necessary to allow the user to pick a sample from the color plane and adjust its lightness with a luminance slider or some other control. In some interfaces, when the luminance slider is moved, the entire plane of colors becomes lighter and darker according to the currently selected level. For those interested in implementing color interfaces, algorithms for a number of color geometries can be found in Foley et al. (1990).

Another valuable addition to a color design interface is a method for showing a color sample on differently colored backgrounds. This allows the designer to understand how contrast effects can affect the appearance of particular color samples.

> **[G4.9]** In an interface for designing visualization color schemes, consider providing a method for showing colors against different backgrounds.

The problem of the best color selection interface is by no means resolved. Experimental studies have failed to show that one way of controlling color is substantially better than another (Schwarz et al., 1987; Douglas & Kirkpatrick, 1996). Douglas and Kirkpatrick, however, have provided evidence that good feedback about the location of the color being adjusted in color space can help in the process.

Color Naming Systems

The facts that there are so few widely agreed upon color names and that color memory is so poor suggest that choosing colors by name will not be useful except for the simplest applications. People agree on red, green, yellow, blue, black, and white as labels, but not much more; nevertheless, it is possible to remember a rather large number of color names and use them accurately under controlled conditions. Displays in paint stores generally have a standard illuminant and standard background for sample strips containing several hundred samples. Under these circumstances, the specialist can remember and use as many as 1000 color names, but many of the names are idiosyncratic; the colors corresponding to *taupe*, *fiesta red*, and *primrose* are imprecisely defined for most of us. In addition, as soon as these colors are removed from the standard booth, they will change their appearance because of illumination-induced adaptation and contrast effects.

The Natural Color System (NCS), a standardized color naming system, has been developed based on Hering's opponent color theory (1920). NCS was developed in Sweden and is widely used in England and other European countries. In NCS, colors are characterized by the amounts of redness, greenness, yellowness, blueness, blackness, and whiteness that they contain. As shown in Figure 4.19, red, green, yellow, and blue lie at the ends of two orthogonal axes. Intervening "pure" colors lie on the circle circumference, and these are given numbers by sharing out 100 arbitrary units; thus, a yellowish orange might be given the value Y70R30, meaning 70 parts yellow and 30 parts red. Colors are also given independent values on a black–white axis by allocating a blackness value between 0 and 100. A third color attribute, intensity (roughly corresponding to saturation), describes the distance from the grayscale axis. In NCS, for example, the color *spring nymph* becomes 0030-G80Y20, which expands to blackness 00, intensity 30, green 80, and yellow 20 (Jackson et al., 1994). The NCS system combines some of the advantages of a color geometry with a reasonably intuitive and precise naming system.

In North America, other systems are more popular than NCS. The Pantone® system is widely used in the printing industry, and the Munsell system is an important reference for surface colors. The Munsell system is useful because it provides a set of standard color chips designed to represent equal perceptual spacing in a three-dimensional mesh. (Munsell color chips and viewing booths are available commercially, as are Pantone products.) The NCS, Pantone, and Munsell systems were originally designed to be used with carefully printed paper samples providing the reference colors, but computer-based interfaces to these systems have been developed as part of illustration

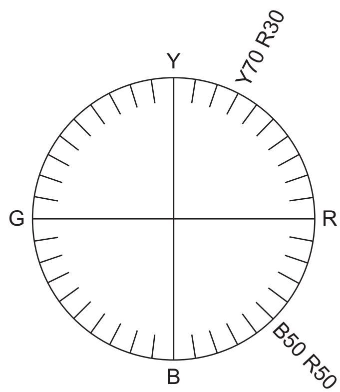

Figure 4.19 The Natural Color System (NCS) circle, defined midway between black and white. Two example color names are shown in addition to the "pure" opponent color primaries. One is an orange yellow and the other is purple.

and design packages. Rhodes and Luo (1996) described a software package that enables transformations between the different systems using the CIE as an intermediate standard.

Color Palettes

When the user wishes to use only a small set of standardized colors, providing a color palette is a good solution to the color selection problem. Often, color selection palettes are laid out in a regular order according to one of the color geometries defined previously. It is useful to provide a facility for the user to develop a personal palette. This allows for consistency in color style across a number of visualization displays.

> **[G4.10]** To support the use of easy-to-remember and consistent color codes, consider providing color palettes for designers.

Sometimes a color palette is based on one of the standard color sets used by the fabric industry or the paint industry. If this is the case, the monitor must be calibrated so that colors actually appear as specified and it must be placed in a standardized viewing environment.

Application 2: Color for Labeling (Nominal Codes)

Suppose we wish to create a visualization where colored symbols represent companies from different industrial sectors—red for manufacturing, green for finance, blue for retail, and so on. The technical name for this kind of labeling is *nominal information coding*. A nominal code does not have to be orderable; it simply must be remembered and recognized. Color can be extremely effective when we wish to make it easy for someone to classify visual symbols into separate categories; giving the objects distinctive colors is often the best solution. One of the reasons why color is often preferred is that the alternatives are generally worse. For example, if we try to create grayscale codes that are easily remembered and unlikely to be confused, we find that four is about the limit: white, light gray, dark gray, and black. Given that white will probably be used for the background and black is likely to be used for text, this leaves only two. In addition, using the gray scale as a nominal code may interfere with shape or detail perception. Chromatic coding can often be employed in a way that only minimally interferes with data presented on the luminance channel. Many perceptual factors must be considered when choosing a set of color labels.

Distinctness. A uniform color space, such as *CIEluv*, can be used to determine the degree of perceived difference between two colors that are placed close together. It might be thought that an algorithm based on *CIEluv* could be used to simply choose a set of colors that are most widely separated, but most color scheme design problems are too complex for this; background colors, symbol sizes, and application-specific requirements all must be taken into account. Also, when we are concerned with the ability to distinguish a color rapidly from a set of other colors, different rules may apply. Bauer et al. (1996) showed that the target color should lie outside the convex hull of the surrounding colors in the CIE color space. This concept is illustrated in Figure 4.20.

Unique hues. The unique hues—red, green, yellow, and blue, as well as black and white—are special in terms of the opponent process model. These colors are also special in the color vocabularies of languages worldwide. Clearly, these colors provide natural choices when a small set of color codes is required.

[G4.11] Consider using red, green, yellow, and blue to color code small symbols.

Contrast with background. In many displays, color-coded objects can be expected to appear on a variety of backgrounds. Simultaneous contrast with background colors can dramatically alter color appearance, making one color look like another. This is one reason why it is advisable to have only a small set of color codes. A method for reducing contrast effects is to place a thin white or black border around the color-coded object. This device is commonly used with signal lights; for example, train signals are displayed on large black background discs. In addition, we should never display codes using purely chromatic differences with the background. There should be a significant luminance difference in addition to the color difference.

[G4.12] For small color-coded symbols, ensure luminance contrast with the background as well as large chromatic differences with the background.

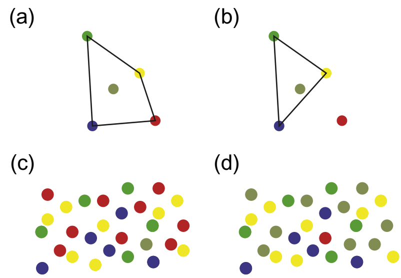

Figure 4.20 The convex hull of a set of colors is defined as the area within a rubber band that is stretched around the colors when they are defined in CIE tristimulus space. Although illustrated in two dimensions here, the concept can easily be extended to three dimensions. (a) Gray is within the convex hull of red, green, yellow, and blue. (b) Red lies outside the convex hull of green, blue, yellow, and gray. (c) The gray dot is difficult to find in a set of red, green, yellow, and blue dots. (d) The red dot is easy to find in a set of green, blue, yellow, and gray dots.

[G4.13] If colored symbols may be nearly isoluminant against parts of the background, add a border having a highly contrasting luminance value to the color, for example, black around a yellow symbol or white around a dark blue symbol.

Figure 4.21 illustrates this principle with a variety of colors against a variety of backgrounds.

Color blindness. Because there is a substantial color-blind population, it may be desirable to use colors that can be distinguished even by people who are color blind. Recall that the majority of color-blind people cannot distinguish colors that differ in a red–green direction. Almost everyone can distinguish colors that vary in a yellow–blue direction, as shown in Figure 4.8. Unfortunately, this drastically reduces the design choices that are available.

[G4.14] To create a set of symbol colors that can be distinguished by most color-blind individuals, ensure variation in the yellow–blue direction.

Figure 4.8 shows the lines defining colors that can be discriminated by most color-blind individuals.

Number. Although color coding is an excellent way to display category information, only a small number of codes can be rapidly perceived. Estimates vary between about five and ten codes (Healey, 1996).

[G4.15] Do not use more than ten colors for coding symbols if reliable identification is required, especially if the symbols are to be used against a variety of backgrounds.

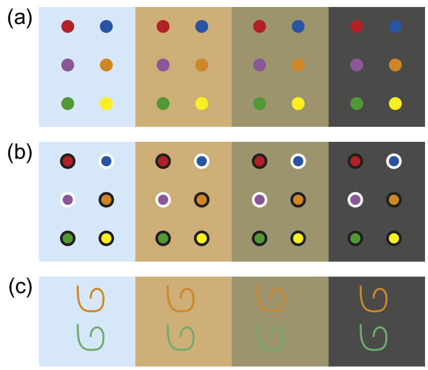

Figure 4.21 (a) Note that at least one member of the set of six symbols lacks distinctness against each background. (b) Adding a luminance contrast border ensures distinctness against all backgrounds. (c) Showing color-coded lines can be especially problematic.

Field size. To avoid the small-field color blindness illustrated in Figure 4.9, do not use very small color-coded areas. In general, the larger the area that is color coded, the more easily colors can be distinguished. Small objects that are color coded should have strong, highly saturated colors for maximum discrimination as already stated in G4.1. When large areas of color coding are used (for example, with map regions), the colors should be of low saturation and differ only slightly from one another. This enables small, vivid color-coded targets to be perceived against background regions.

[G4.16] Use low-saturation colors to color code large areas. Generally, light colors will be best because there is more room in color space in the high-lightness region than in the low-lightness region.

[G4.17] When color coding large background areas overlaid with small colored symbols, consider using all low-saturation, high-value (pastel) colors for the background, together with high-saturation symbols on the foreground.

Figure 4.22 shows two examples, one that follows these guidelines and one that contradicts them.

The goal of highlighting is to make some small subset of a display clearly distinct from the rest, and the same principles apply to the highlighting of text or other features in a display.

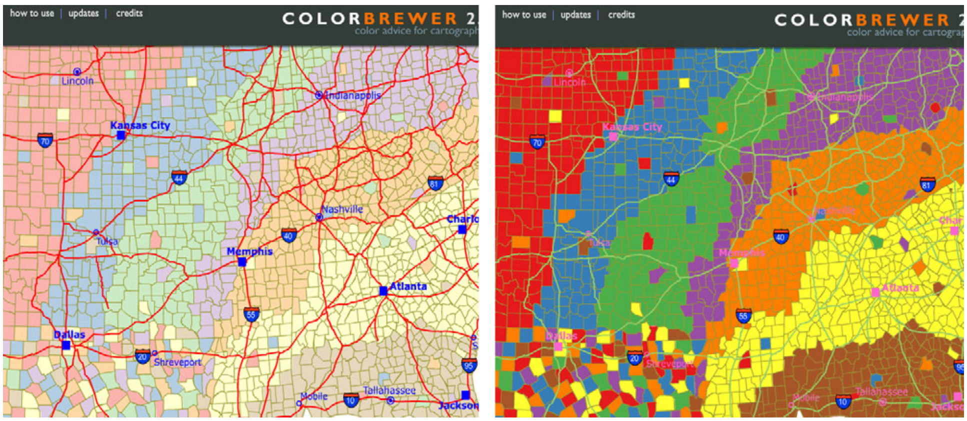

Figure 4.22 On the left is a map using low-saturation light colors for the area coding and high-saturation dark colors for the town and city symbols and linear features. On the right, a much worse solution shows high-saturation coding for areas and low-saturation symbols and linear features. Maps were generated using ColorBrewer2 (http://colorbrewer2.org).

[G4.18] When highlighting text by changing the color of the font, it is important to maintain luminance contrast with the background. With a white background, high-saturation dark colors must be used to change the font color. Alternatively, when changing the background color, low-saturation light colors should be used if the text is black on white.

Figure 4.23 illustrates these two alternatives.

Conventions. Color-coding conventions must sometimes be taken into account. Some common conventions are red = hot, red = danger, blue = cold, green = life, and green = go. It is important to keep in mind, however, that these conventions do not necessarily cross cultural borders. In China, for example, red means life and good fortune, and green sometimes means death.

The following is a list of 12 colors recommended for use in coding: red, green, yellow, blue, black, white, pink, cyan, gray, orange, brown, purple. They are illustrated in Figure 4.24. These colors have widely agreed upon category names and are reasonably far apart in color space. The first four colors, together with black and white, are chosen because they are the unique colors that mark the ends of the opponent color axes. The entire set corresponds to the 11 color names found to be the most common in the cross-cultural study carried out by Berlin and Kay (1969), with the addition of cyan.

(a) Higlighting text by changing the characters must be done using high saturation colors that contrast with the background.

(b)

```
import java.applet.Applet;
import java.awt.Graphics;
import java.awt.Color;

    public class ColorText extends Applet
{
    public void init()
    {
            red = 100;
            green = 255;
            blue = 20;
    }
    public void paint (Graphics g)
    {
            Gr.setColor(new Color(red, green, blue));

            Gr.drawString("ColoredText". 30,50);
    }

    private int red;
    private int green;
    private int blue;
}
```

Figure 4.23 Two different methods for highlighting black text. (a) Change text itself using a relatively dark, high-saturation color. (b) Change text background using low-saturation light colors. Both maintain luminance contrast.

The colors in the first set of six would normally be used before choosing any from the second set of six.

Sometimes it is useful to group color codes into families. This can be done by using hue as a primary attribute denoting family membership, with secondary values mapped to a combination of saturation and lightness. Figure 4.25 illustrates some examples. Generally, we cannot expect to get away with more than two different color steps in each family. The canonical red, green, and blue hues make good categories for defining families. Yellow is not so good because dark yellow is perceived as belonging to a different family and yellow has few discriminable saturation steps. Family members then can be distinguished from one another by saturation, as in Figure 4.25(a), or, even better, by saturation and lightness, as in Figure 4.25(b). Interior designers often consider a family of warm colors (nearer to red in color space) to be distinct from a family of cool colors (nearer to blue and green in color space), although the psychological validity of this is questionable.

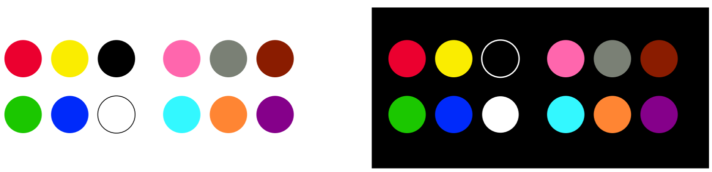

Figure 4.24 A set of 12 colors for use in labeling. The same colors are shown on a white and a black background.

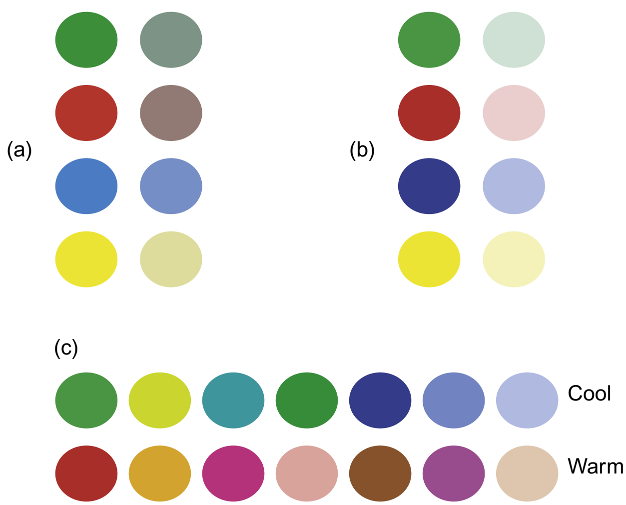

Figure 4.25 Families of colors. (a) Pairs related by hue; family members differ in saturation. (b) Pairs related by hue; family members differ in saturation and lightness. (c) A family of cool hues and a family of warm hues.

Application 3: Color Sequences for Data Maps

Somewhere in almost every newspaper and on every weather website is a map where regions are colored differently to show the forecast temperatures. Red is used to show hot weather, blue is used to show cold weather, and other colors are arranged in between, often using the colors of the rainbow, blue–cyan–green–yellow–orange–red.

Pseudocoloring is the technique of representing continuously varying map values using a sequence of colors. The result is sometimes called a *choropleth* map. Pseudocoloring is used widely for astronomical radiation charts, medical imaging, and many other scientific applications. Geographers use a well-defined color sequence to display height above sea level—lowlands are always colored green, which evokes vegetation, and the scale continues upward, through brown, to white at the peaks of mountains.

The most common coding scheme used in data visualization is a color sequence that approximates the physical spectrum, like that shown in Figure 4.26(b). Although this sequence is frequently used in physics and other disciplines and has some useful properties, it is not a perceptual sequence. This can be demonstrated by the following test. Give someone a series of gray paint chips and ask them to place them in order. They will happily comply with either a dark-to-light ordering or a light-to-dark ordering. Give the same person paint chips with the colors red, green, yellow, and blue and ask them to place them in order, and the result will be varied. For most people, the request will not seem particularly meaningful. They may even use an alphabetical ordering. This demonstrates that the whole spectrum is not perceptually ordered, although short sections of it are. For example, sections from red to yellow, yellow to green, and green to blue all vary monotonically (they continuously increase or decrease) on both the red–green and yellow–blue channels. Figure 4.27 shows seven different color sequences, but which is best and why?

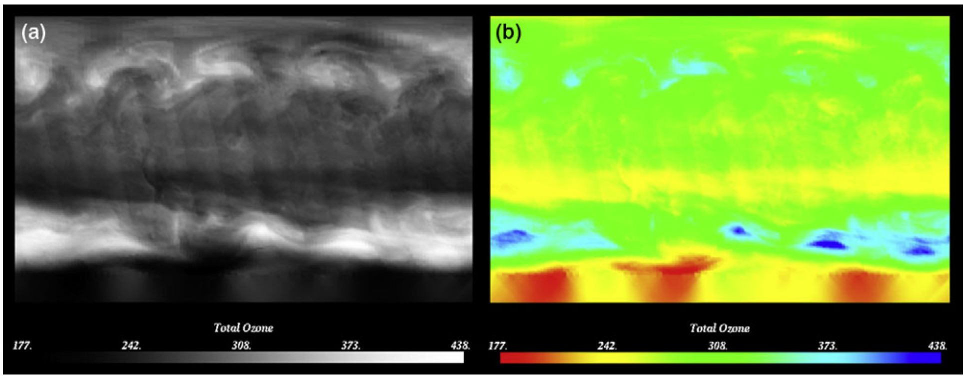

Figure 4.26 The same data showing ozone concentrations in the southern hemisphere is represented using (a) grayscale and (b) spectrum approximation pseudocolor sequences. (*Images courtesy of Penny Rheingans (Rheingans, 1999).*)

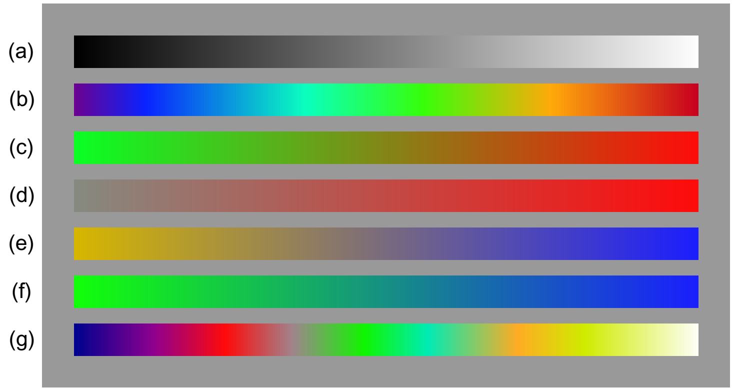

Figure 4.27 Seven different color sequences: (a) Grayscale. (b) Spectrum approximation. (c) Red–green. (d) Saturation. (e, f) Two sequences that will be perceived by people suffering from the most common forms of color blindness. (g) Sequence of colors in which each color is lighter than the previous one.

Form and Quantity

Sometimes we want to see the forms in a data set. Where are the highs and lows, the ridges and spirals, in a map of ozone in the atmosphere? Sometimes we want to be able to read the quantities. What is the temperature going to be in my part of the world tomorrow?

Color theory predicts that different color sequences have very different properties in this regard (Ware, 1988). Because the luminance channel helps us see forms, a grayscale sequence should allow us to see forms much better than pure color sequences (no luminance variation). See Figure 4.26(a). The highs are white, the lows are black, and complex swirling patterns can be seen in the ozone concentrations. Look at Figure 4.26(b). Here red, green, and blue areas clearly stand out, but this visual segmentation is meaningless; it is not clear which areas are high and low, and much less detail is seen overall.

Experimental studies have confirmed that grayscale maps are much better for form perception (Ware, 1988; Kindlmann et al., 2004). In spite of this, a recent survey of papers containing pseudocolored maps found that more than 50% used an approximation to the physical spectrum—a rainbow as a color sequence (Borland & Taylor, 2007). The same paper argued that this color sequence "*hinders this task* [of effectively conveying information] *by confusing, obscuring, and actively misleading.*"

Nevertheless, there are advantages to the spectrum approximation color sequence. The first is that it results in much lower errors in reading values from a key. Ware (1988) found 17% scale errors with a grayscale map and only 2.5% error with a spectrum approximation. There are two reasons for this. A spectrum color sequence can convey significantly more legible steps than a simple blue-to-red sequence (that is sometimes used for coding temperature).

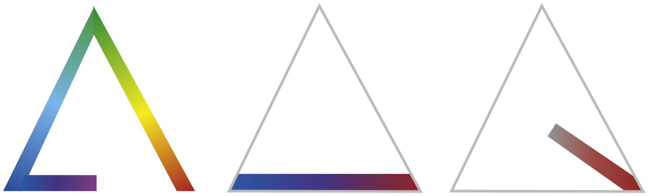

Figure 4.28 Sequences on a chromaticity diagram. (a) Spectrum approximation. (b) Blue–red sequence. (c) Saturation sequence.

Consider the sequences illustrated in Figure 4.28. These are based on the *RBG* triangle in the *CIEluv* uniform color space. A typical spectrum sequence actually starts with purple (not a true spectrum hue) and cycles clockwise through the spectrum colors to red. This path has more than two and a half times as many discriminable steps according to *CIEluv* than the red–blue sequence, and it has four times as many legible steps as a saturation sequence. Also, according to the *CIEluv* and *CIElab* color difference standards, there are about twice as many discernable steps in a traversal across the chromatic dimensions of color space as there are traversing the luminance dimension (Mahny, 1994). Another cause of errors in reading map values using a key is simultaneous contrast between parts of the display (Cleveland & McGill, 1983; Ware, 1988; Brewer, 1996b). These errors may be reduced in the spectrum sequence scale because the colors surrounding a particular point (and inducing contrast effects) are likely to partially cancel each other.

There are also sometimes semantic reasons for using a spectrum approximation sequence. Consider the case of the display of temperature in weather maps. The color blue is associated with cold. The color red is associated with heat. Having green and yellow in between provides a convenient method for conveying intermediate temperatures. In the case of a weather map, and many other visualizations, the ability to read quantity as well as see patterns in the data is essential. We may need to be able to read temperatures to better than 5 degrees over a 50-degree or greater range. This requires ten or more discriminable steps, something that is impossible to achieve with the blue-to-red sequence. Finally, the use of spectrum approximations for temperature maps is deeply embedded in large parts of our culture. Using this well-established standard can have huge efficiencies because it eliminates the need to learn something new.

[G4.19] Use a spectrum approximation pseudocolor sequence for applications where its use is deeply embedded in the culture of users. This kind of color sequence can also be used where the most important requirement is reading map values using a key. If this sequence is used, the spacing of the colors should be carefully chosen to provide discriminable steps.

Still, if it is important to show detail in the data, then it is essential to make that detail stand out using the luminance (black–white) channel because of the capacity of this channel to convey high-spatial-frequency information (Ware, 1988; Rogowitz & Treinish, 1996). Also, if form perception is the primary consideration, a sequence that trends upward or downward in luminance will be better.

Some authors have recommended that, for clarity, color sequences should constitute a straight line through a perceptual color space, such as *CIEluv* or *CIElab* (Robertson & O'Callaghan, 1988; Levkowitz & Herman, 1992). This would rule out the spectrum approximation sequence. Further, Spence et al. (1999) found that a color sequence combining variation in brightness, saturation, and hue was the most effective in a task requiring the rapid detection of low and high points in an image.

A better choice may be to design a sequence that cycles through a variety of colors, each one lighter than the previous. Sometimes this is called a *spiral color sequence*, because it can be thought of as spiraling upward in color space. Such a sequence can combine the advantages of monotonicity in luminance, so as to show form and detail, as well as reduce contrast-induced errors and enable accurate readings from a color key (Ware, 1988; Levkowitz & Herman, 1992; Kindelmann et al., 2004).

> **[G4.20]** If it is important to see highs, lows, and other patterns at a glance, use a pseudocolor sequence that monotonically increases or decreases in luminance. If reading values from a key is also important, cycle through a variety of hues while trending upward or downward in luminance.

The designer of such a sequence can take advantage of the fact that monitor blue has much lower luminance than monitor red, which in turn has lower luminance than monitor green. Yellow, being the sum of red and green, has a very high luminance, almost equal to white. This is the basis for the sequence design shown on the right in Figure 4.29.

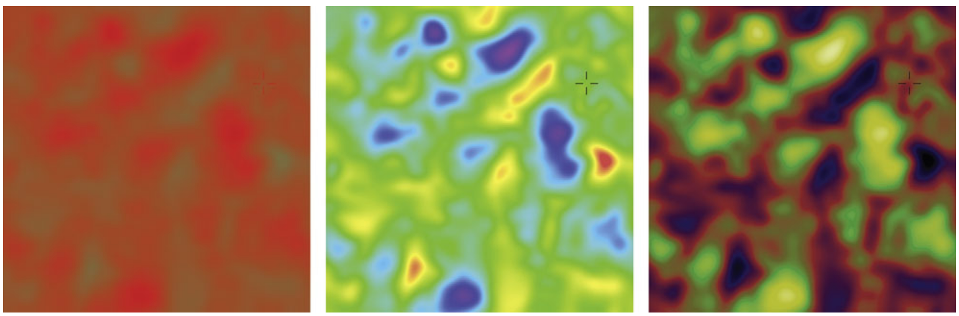

Figure 4.29 The same data represented with saturation, spectrum, and spiral color sequences. The spiral sequence makes it possible to easily see both the highs and lows, as well as read values accurately from a key.

Interval Pseudocolor Sequences

An interval sequence is one in which each unit step of the sequence represents an equal change in magnitude of the characteristic being displayed across the whole range of the sequence. In terms of color, this suggests using a uniform color space in which equal perceptual steps correspond to equal metric steps (Robertson & O'Callaghan, 1988). Using a contour map, not a color sequence, is the traditional way to display an interval sequence. Isovalue contour maps show the pattern of equal heights or other physical attributes with great precision, but using them to understand the overall shape of a terrain or an energy field takes considerable skill and experience. To support unskilled map readers, contours can be usefully combined with pseudocoloring, as shown in Figure 4.30(a). Even better may be a stepped pseudocolor sequence as shown in Figure 4.30(b).

Ratio Pseudocolors

A ratio sequence is an interval sequence that has a true zero and all that this implies: The sign of a value is significant; one value can be twice as large as another. Expressing this in a color sequence is a tall order. No known visualization technique is capable of accurately conveying ratios with any precision; however, a sequence can be designed that effectively expresses a zero point and numbers above and below zero. Brewer (1996a) called such sequences *diverging sequences*, whereas Spence and Efendov (2001) called them *bipolar sequences*. Such sequences typically use a neutral value on one or more

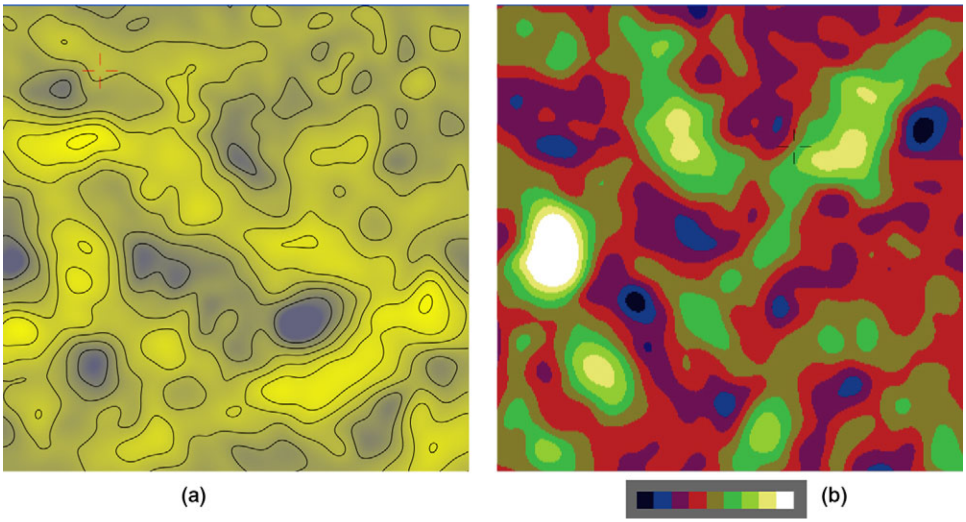

Figure 4.30 (a) Contours can show equal intervals in the data although numerical labels must be added for most applications. (b) A sequence of colors in discrete steps may be more reliably read using a key than a smoothly blended sequence.

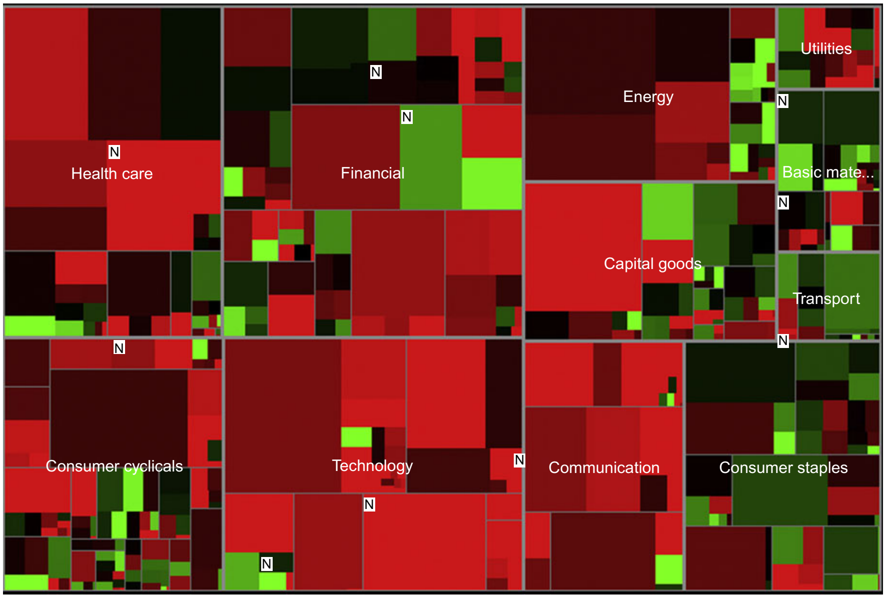

Figure 4.31 A color sequence with black representing zero. Increasing positive values are shown by increasing amounts of red. Increasing negative values are shown by increasing amounts of green. The map itself is a form of treemap (Johnson & Shneiderman, 1991). (*Courtesy of SmartMoney.com.*)

opponent channels to represent zero, and diverging colors (on one or more channels) to represent positive and negative quantities. For example, gray may be used to represent zero, increasing redness to represent positive quantities, and increasing blueness to represent negative quantities. In a target detection study, Spence and Efendov (2001) found that a red–green sequence was most effective, confirming the greater information-carrying capacity of this channel compared to the yellow–blue channel.

The example in Figure 4.31 shows a map of the stock market provided by SmartMoney .com. Market capitalization is represented by area, luminance encodes the magnitude of value change in the past year, and green–red encodes gains and losses. The website also gives users the option of a yellow–blue coding, suitable for most color-blind individuals.

Sequences for the Color Blind

Some color sequences will not be perceived by people who suffer from the common forms of color blindness: protanopia and deuteranopia. Both cause an inability to discriminate red from green. Sequences that vary mainly on a black-to-white scale or on a yellow-to-blue dimension (this includes green to blue and red to blue) will still be clear to color-blind people. Two sequences that will be acceptable to these individuals are shown in Figure 4.27(e, f). Meyer and Greenberg (1988) provided a detailed analysis of color sequences designed for common forms of color blindness.

Bivariate Color Sequences

Because color is three dimensional, it is possible to display two or even three dimensions using pseudocoloring (Trumbo, 1981). Indeed, this is commonly done in the case of satellite images, in which invisible parts of the spectrum are mapped to the red, green, and blue monitor primaries.

Although this mapping is simple to implement and corresponds to capabilities of the display device (which usually has red, green, and blue phosphors), such a scheme does not map the data values to perceptual channels. In general, it is better to map data dimensions to perceptual color dimensions. For example:

Variable one → hue

Variable two → saturation

or

Variable one → hue

Variable two → lightness

Figure 4.32 gives an example of a bivariate color sequence from Brewer (1996a) that maps one variable to yellow–blue variation and the other to a combination of light–dark variation and saturation. It suffers from the usual problem that the low-saturation colors are difficult to distinguish.

As a word of caution, it should be noted that bivariate color maps are notoriously difficult to read. Wainer and Francolini (1980) carried out an empirical evaluation of a color sequence designed for U.S. census data and found that it was essentially unintelligible. One approach to a solution is to apply a uniform color space, and Robertson and O’Callaghan (1986) discussed how to do this. But, distinctness may not lead to something that is interpretable. We do not seem to be able to read different color dimensions in a way that is highly separable.

Pseudocoloring is not the only way to display a two-dimensional scalar field. Generally, when the goal is to display two variables on the same map, it may be better to use visual texture, height difference, or another channel for one variable and color for the other, in this way mapping data dimensions to more perceptually separable dimensions. Mapping the scalar field to artificial height and shading the resulting surface with an artificial light source using standard computer graphics techniques is another alternative. These methods are discussed later in the book.

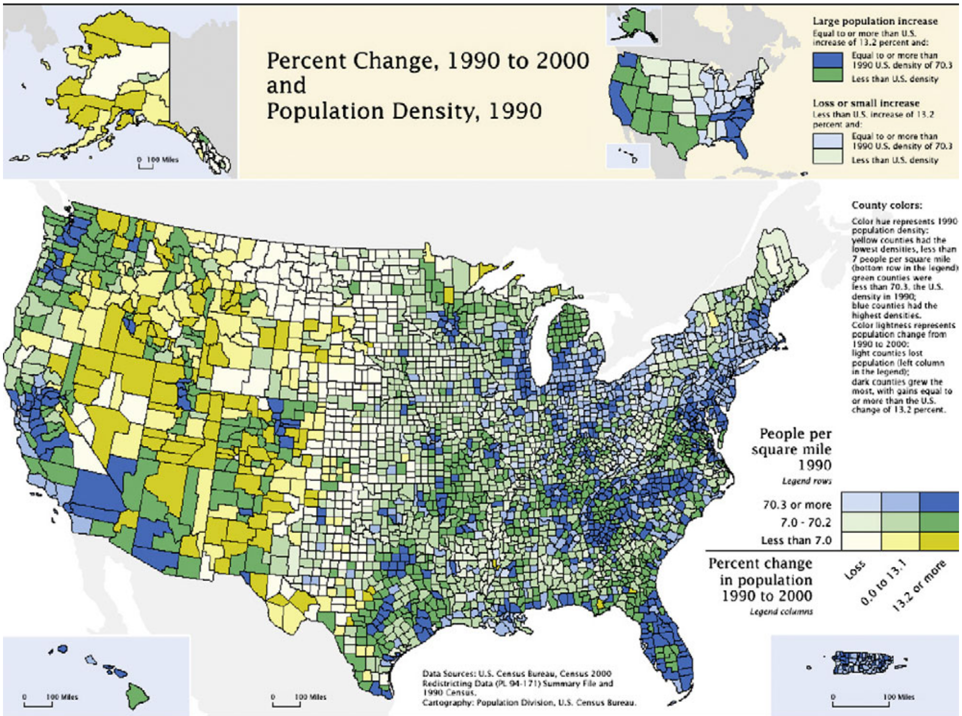

Figure 4.32 A bivariate coloring scheme using saturation and lightness for one variable and yellow–green–blue hue variation for the other. (*Courtesy of Cindy Brewer.*)

Many considerations go into making a color sequence that displays quantities without significant distortions, and this makes it unlikely that any predefined set of colors will exactly suit a particular data set and visualization goal. To show both overall form and detail and to provide the ability to read values from a key, it is often desirable to emphasize certain features in the data by deliberately using a nonuniform sequence; assigning more variation in color to a particular data range will lead to its visual emphasis and better discrimination of those values. Generally, the best way to achieve an effective color sequence is to place a good color editing tool in the hands of someone who understands both the data display requirement and the perceptual issues of color sequence construction (Guitard & Ware, 1990).

Application 4: Color Reproduction

The problem of color reproduction is essentially one of transferring color appearances from one display device, such as a computer monitor, to another device, such as a sheet of paper. The colors that can be reproduced on a sheet of paper depend on such factors as the color and intensity of the illumination. Northern daylight is much bluer than direct sunlight or tungsten light, which are both quite yellow, and is prized by artists for this reason. Halogen light is more balanced. Also, monitor colors can be reproduced only within the range of printing inks; therefore, it is neither possible nor meaningful to reproduce colors directly using a standard measurement system such as the CIE XYZ tristimulus values.

As we have discussed, the visual system is built to perceive relationships between colors rather than absolute values. For this reason, the solution to the color reproduction problem lies in preserving the color relationships as much as possible, not the absolute values. It is also important to preserve the white point in some way, because of the role of white as a reference in judging other colors.

Stone et al. (1988) described a process of gamut mapping designed to preserve color appearance in a transformation between one device and another. The set of all colors that can be produced by a device is called the *gamut* of that device. The gamut of a monitor is larger than that of a color printer (roughly the gamut of surface colors shown in Figure 4.7). Stone et al. described the following set of heuristic principles to create good mapping from one device to another:

1. The gray axis of the image should be preserved. What is perceived as white on a monitor should become whatever color is perceived as white on paper.

2. Maximum luminance contrast (black to white) is desirable.

3. Few colors should lie outside the destination gamut.

4. Hue and saturation shifts should be minimized.

5. An overall increase of color saturation is preferable to a decrease.

Figure 4.33 illustrates, in two dimensions, what is in fact a three-dimensional set of geometric transformations designed to accomplish the principles of gamut mapping. In this example, the process is a transformation from a monitor image to a paper hard copy, but the same principles and methods apply to transformations between other devices.

- **Calibration.** The first step is to calibrate the monitor and the printing device in a common reference system. Both can be characterized in terms of CIE tristimulus values. The calibration of the color printer must assume a particular illuminant.

- **Range scaling.** To equate the luminance range of the source and destination images, the monitor gamut is scaled about the black point until the white of the monitor has the same luminance as the white of the paper on the target printer.

- **Rotation.** What we perceive as neutral white on the monitor and on the printed paper can be very different, depending on the illumination. In general, in a printed image, the white is defined by the color of the paper. Monitor white is usually defined by the color that results when the red, green, and blue monitor primaries are set to their maximum values. To equate the monitor white with the paper white, the monitor gamut is rotated so as to make the white axes colinear.

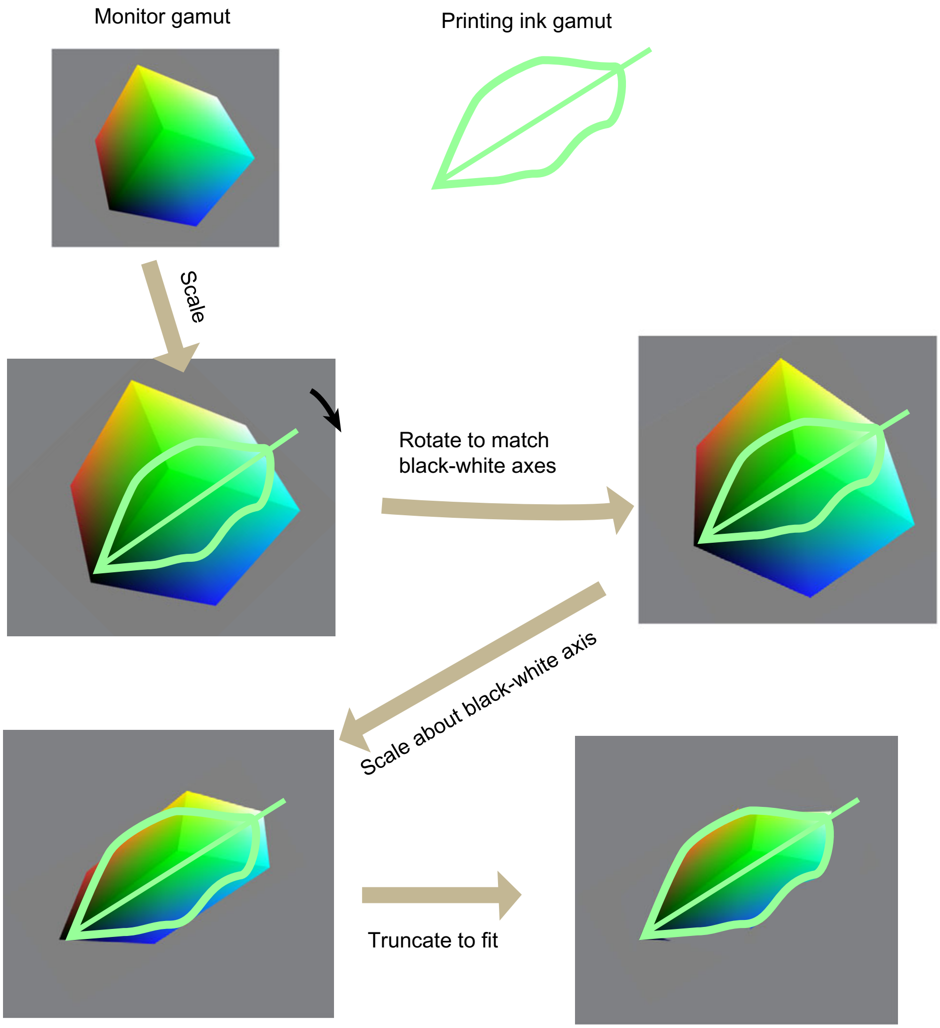

Figure 4.33 Illustration of the basic geometric operations in gamut mapping between two devices, as defined by Stone et al. (1988).

- **Saturation scaling.** Because colors can be achieved on a monitor that cannot be reproduced on paper, the monitor gamut is scaled radially with respect to the black–white axis to bring the monitor gamut within the range of the printing gamut. It may be preferable to leave a few colors outside the range of the target device and simply truncate them to the nearest color on the printing-ink gamut boundary.

For a number of reasons, it may not always be possible to apply these rules automatically. Different images may have different scaling requirements; some may consist of pastel colors that should not be made too vivid, whereas others may have vivid colors that must be truncated.

The approach adopted by Stone et al. (1988) is to design a set of tools that support these transformations, making it easy for an educated technician to produce a good result; however, this elaborate process is not feasible with off-the-shelf printers and routine color printing. In these cases, the printer drivers will contain heuristics designed to produce generally satisfactory results. They will contain assumptions about such things as the gamma value of the monitor displaying the original image and methods for dealing with oversaturated colors. Sometimes, the heuristics embedded in devices can lead to problems. In our laboratory, we usually find it necessary to start a visualization process with somewhat muted colors to avoid oversaturated colors on videotape or in paper reproduction.

Another issue that is important in color reproduction is the ability of the output device to display smooth color changes. Neural lateral inhibition within the visual system tends to amplify small artificial boundaries in smooth gradients of color as Mach bands. This sensitivity makes it difficult to display smoothly shaded images without artifacts. Because most output devices cannot reproduce the 16 million colors that can be created with a monitor, considerable effort has gone into techniques for generating a pattern of color dots to create the overall impression of a smooth color change. Making the dots look random is important to avoid aliasing artifacts (discussed in Chapter 2). Unless care is taken, artifacts of color reproduction can produce spurious patterns in scientific images.

Conclusion

There has been more research on the use of color in visualization than any other perceptual issue. Nevertheless, the important lessons are relatively few, and mostly they can be derived from opponent process theory. There are two chromatic channels (red–green and yellow–blue) and a luminance channel. Because of the low spatial resolution of the chromatic channels, small symbols should have high-saturation colors. Because of chromatic contrast in the opponent channels, we can only expect to have a few color symbols reliably identifiable. Contrast effects also make it desirable that larger regions should be less strongly colored in general.

It is impossible to keep a discussion of color entirely segregated in one chapter. Color affects every aspect of visualization and is mentioned in many other chapters, especially Chapter 5, which places color in the context of other methods for coding information.

CHAPTER FIVE

Visual Salience and Finding Information

Suppose there is a crisis at a large bank because an employee, George, has lost billions on risky stock trades. We need to identify the vice president who is responsible for George's activities, and we have at our disposal an organization chart showing the management hierarchy of the company. This problem can be solved through a straightforward visual thinking process. First, conduct a visual search for the box representing George, then visually trace upward, following the chain of lines and boxes up to the level of vice president.

Another example: Suppose we are looking at the floor plan of a museum building and we wish to find a coffee shop. We locate the symbol for coffee shop on the key at the side of the floor plan, and then we carry out a visual search to find that symbol on the plan. A second more complex visual thinking process will be needed to find a route from where we are currently to the location of our coffee.

In both of these examples, a core activity can be described in terms of a two-step process:

> **Step 1.** A visual query is formulated in the mind of the person, relating to the problem to be solved.
>
> **Step 2**. A visual search of the display is carried out to find patterns that resolve the query.

The visual query can have many different forms, but it always involves reformulating part of the problem so that the solution can be found through a visual pattern search.

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The visual pattern to be found can range from a symbol of a particular shape or color to an arbitrary complex or subtle visual pattern. In all cases, understanding what makes a pattern easy to find is critical in determining how efficiently the query will be executed, and what makes for efficient search is the central theme of this and the next chapters. In explaining this we will be putting flesh on the bare bones of the first two guidelines of this book set out in Chapter 1 and restated here to save the need to look back. [G1.1] *Design graphic representations of data by taking into account human sensory capabilities in such a way that important data elements and data patterns can be quickly perceived.* [G1.2] *Important data should be represented by graphical elements that are more visually distinct than those representing less important information.*

In understanding how visual queries are resolved we gain a deeper understanding of how best to design two of the most common kinds of things used in data visualization—namely, graphical *symbols* and *glyphs*. A graphical *symbol* is a *graphical object that represents an entity*. An example is the coffee shop symbol on the map. If this were to look like a coffee cup it would be an *iconic* symbol. Other examples are the noniconic triangles and squares used to represent data points in statistical graphs. A well-designed symbol set is one where each of the symbols can be readily found, each symbol is distinct from the others, and each symbol is compact.

Whereas symbols have a purely nominal function, *glyphs* also represent quantitative values. A *glyph* is a *graphical object designed to represent some entity and convey one or numerical attributes of that entity*. For information about stocks on the stock exchange, the color of a glyph can be used to show the price-to-earnings ratio, the size of the glyph can display the growth trend, and the shape of the glyph can represent the type of company—square for technology stocks, round for resources, and so on. A well-designed glyph is one that, in addition to being easily found, supports rapid and accurate resolution of visual queries regarding the ordinal, interval, or ratio quantities that are expressed.

Visual search is one of the basic things the visual system is designed for, and it involves the entire visual system. A large part of search is the way the eyes are moved around the scene to pick up information, but as we shall see it also involves the retuning of every visual part of the brain to meet the needs of the query task. There is a kind of mental inner scan, within a fixation, where a few visual patterns are tested for query-resolving properties. We will start with some basic facts about eye movements and then go on to discuss the factors that make something a target of an eye movement, before returning to the overall process.

Eye Movements

Moving our eyes causes different parts of the visual environment to be imaged on the high-resolution fovea where we can see detail. Eye movements are frequent. For example, as you read this page, your eye is making between two and five jerky movements, called *saccades*, per second, and each of these movements can be thought of as a basic act of visual search.

There are three important types of eye movements:

1. **Saccadic movements.** In a visual search task, the eye moves rapidly from fixation to fixation. The dwell period is generally between 200 and 400 msec; the saccade takes between 20 and 180 msec and depends on the angle moved. For eye movements of more than 20 degrees, head movements follow, and this can take half a second or more (Hallett, 1986; Barfield et al., 1995; Rayner, 1998). A typical length of a saccade for someone scanning a scene is about 5 degrees of visual angle. A typical length of a saccade when reading is 2 degrees (Land & Tatler, 2009). The typical length of the saccade that people make when using visualizations depends on the design and the size of the display, but we can expect it to be in the range of 2 to 5 degrees for a well-designed display. As a general principle, visual search will be considerably more efficient for more compact displays because eye movements will be shorter and faster.

[G5.1] To minimize the cost of visual searches, make visualization displays as compact as possible, compatible with visual clarity. For efficiency, information nodes should be arranged so that the average saccade is 5 degrees or less.

2. **Smooth-pursuit movements.** When an object is moving smoothly in the visual field, the eye has the ability to lock onto it and track it. This is called a *smooth-pursuit* eye movement. This ability also enables us to make head and body movements while maintaining fixation on an object of interest.
3. **Convergent movements (also called vergence movements).** When an object moves toward us, our eyes converge. When it moves away, they diverge. Convergent movements can be either saccadic or smooth.

Saccadic eye movements are said to be *ballistic*. This means that once the brain decides to switch attention and make an eye movement, the muscle signals for accelerating and decelerating the eye are preprogrammed; the movement cannot be adjusted in mid-saccade. During a saccadic eye movement, we are less sensitive to visual input. This is called *saccadic suppression* (Riggs et al., 1974). The implication is that certain kinds of events can easily be missed if they occur while we happen to be moving our eyes. This is important when we consider the problem of alerting a computer operator to an event.

Another implication of saccadic suppression is that the brain is usually processing a rapid sequence of discrete images. Our capacity to do this is increasingly being exploited in television advertising, in which more than one cut per second of video has become commonplace. More generally, the staccato nature of seeing means that what we can see *at a single glance* is tremendously important.

Accommodation

For completeness, a different kind of adjustment also requires mention before we move on. When the eye moves to a new target at a different distance from the observer, it must refocus, or accommodate, so that the target is clearly imaged on the retina. An accommodation response typically takes about 200 msec. As we age, however, the ability to accommodate declines and refocusing the eyes must be accomplished by changing eyeglasses or, for users of bifocals or progressive lenses, by moving the head so that a different lens is between the pupil and the object being fixated. Another solution is to use laser surgery to make one eye have a near focus and the other a far focus. In this case, change of focus is accomplished by switching attention from one eye's input to the other. This is a skill that must be learned.

The Eye Movement Control Loop

Seeing can be thought of as a never-ending series of cognitive acts, each of which has the same structure: make an eye movement, pick up some information, interpret that information, and plan the next eye movement. Sometimes the planning occurs in parallel with the interpretation. Figure 5.1 summarizes the major components of this process. As a first step, search queries are constructed to help with whatever task is at hand, and these typically consist of the cognitive construction of a simple pattern to be found. The next step is a visual search for that pattern.

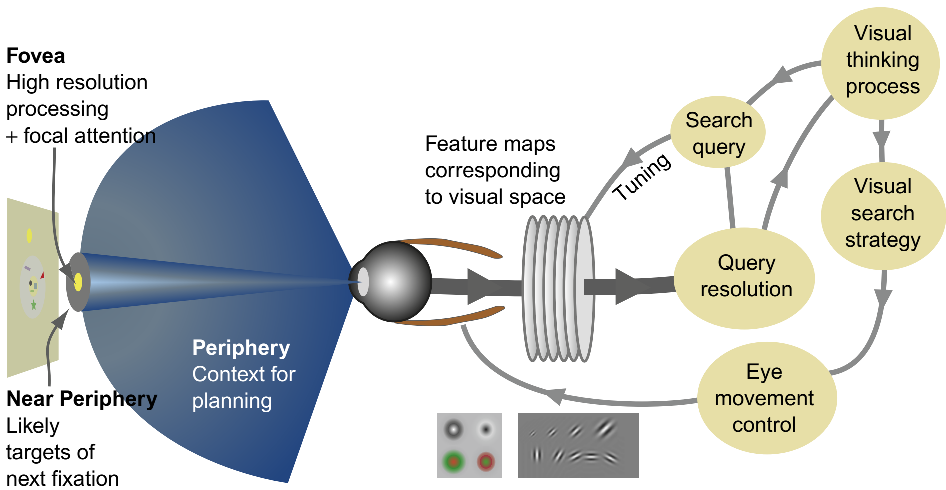


Figure 5.1 The visual search process.

But, how can the brain prepare for an eye movement without already knowing what is at the target location? How do we know where to look next? According to the theory of Wolfe and Gancarz (1996), a heuristic strategy is employed. First, a set of feature maps of the entire visual field is produced in a parallel processing operation mostly done in the V1 area of the primary visual cortex. Each feature map is devoted to a particular kind of feature, for example, vertical contours, blobs of a particular size, or a particular color. Each map is weighted according to the current task. If we are scanning a crowd to look for someone we know who has a yellow raincoat, the feature maps will emphasize yellow blobs. Next, eye movements are executed in sequence, visiting the strongest possible target area (as defined by the feature maps) first and proceeding to the next strongest. Eye movements are also weighted according to the distance from the current focus along with other strategic factors.

Three things determine what is easily findable:

1. ***A priori* salience.** Some patterns excite more neural activity in the feature maps than others.
2. **Top-down salience modification.** Depending on what we are looking for, top-down mechanisms retune the feature maps to increase their sensitivity to certain features; for example, we may wish to find a mostly vertical elongated symbol. The vertical orientation feature map will gain enhanced sensitivity.
3. **Scene gist.** This has less to do with feature maps and more to do with experience. It is something that is discussed in Chapter 11 in the context of eye movement control strategies. The important point for now is that the brain very rapidly recognizes the type of scene that is being viewed (store interior, open landscape, city street), allowing it to activate visual search strategies appropriate to a visual scene (Oliva et al., 2003). If a type of visualization is well known, then the eye movement strategies will be automatically primed for activation. This is part of the skill we develop in repeatedly using a particular style of visualization.

The perceptual mechanisms relating to V1 and V2 are the subject of this chapter, together with the lessons we can learn from them. The lessons of scene gist and the overall strategy can be found in later chapters when we discuss the skills of visual thinking.

V1, Channels, and Tuned Receptors

After preliminary processing in the retina of the eye, visual information passes up the optic nerve through a neural junction at the lateral geniculate nucleus (LGN) and through several stages of processing in the cortex. The first areas in the cortex to receive visual inputs are called, simply, *visual area 1* (V1) and *visual area 2* (V2). Most of the output from area 1 goes on to area 2, and together these two regions make up more than 40% of vision processing (Lennie, 1998). There is plenty of neural processing power, as several billion neurons in V1 and V2 are devoted to analyzing the signals from only 2 million nerve fibers coming from the optic nerves of two eyes. This makes possible the massively parallel simultaneous processing of the entire visual field for incoming signals for color, motion, texture, and the elements of form. It is here that the elementary vocabularies of both vision and data display are defined.

By the time it gets to the LGN, the signal has already been decomposed by the concentric receptive fields discussed in the previous chapter that convert the signal into red–green, yellow–blue, and dark–light differences. These signals are then passed on to V1 where slightly more complex patterns are processed.

Figure 5.2 is derived from Livingston and Hubel's diagram (1988) that summarizes both the neural architecture and the features processed in V1 and V2. A key concept in understanding this diagram is the tuned receptive field. In Chapter 3, we saw how single cell recordings of cells in the retina and the LGN reveal cells with distinctive concentric receptive fields. Such cells are said to be tuned to a particular pattern of a white spot surrounded by black or a black spot surrounded by white. In general, a tuned filter is a device that responds strongly to a certain kind of pattern and responds much less, or not at all, to other patterns. In the primary visual cortex, some cells respond only to elongated blobs with a particular position and orientation, others respond most strongly to blobs of a particular position moving in a particular direction at a particular velocity, and still others respond selectively to color.

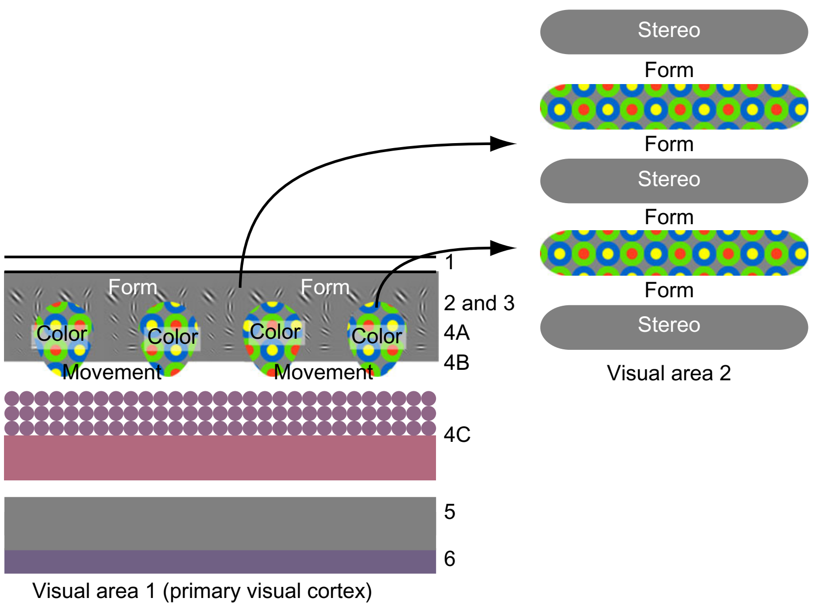


Figure 5.2 Architecture of the primary visual cortex. (*Redrawn from Livingston & Hubel (1988)*.)

There are cells in V1 and V2 that are differentially tuned to each of the following properties:

- Orientation and size (with luminance) via the Gabor processor described later in this chapter
- Color (two types of signals) via the opponent processing channel mechanisms discussed in Chapter 4
- Elements of local stereoscopic depth
- Elements of local motion

In V1 and V2 and many other regions of the brain, neurons are arranged in the form of a spatial map of the retina, meaning that adjacency relationships are preserved. A feature that is close to another feature in the image on the retina is processed by nearby neurons in V1. These maps are highly distorted, however, because the fovea is given far more space in the cortex than regions in the periphery of vision. In cortical regions devoted to the fovea, receptive fields are much smaller. It is a system in which, for each point in visual space, neurons are tuned for many different orientations, many different kinds of color information, many different directions and velocities of motion, and many different stereoscopic depths.

Notice that here we have been talking about V1 as containing a single map of the visual field, but in fact it contains a set of semi-independent feature maps, all spatially co-registered.

The Elements of Form

It is useful to think of the things that are extracted by early stage visual processing as the elements of form and pattern perception. Phonemes are the smallest elements in speech recognition, the components from which meaningful words are made. In a similar way, we can think of orientation detectors, color detectors, and so on as the elements from which meaningful perceptual objects are constructed.

An important point that can be derived from Figure 5.3 is that color and the elements of form (orientation and size) are processed separately and therefore are easy to visually separate. It is also the case that moving patterns are visually separate from static patterns. These different properties are said to have different *channels*, meaning that information expressed in one channel, the color of a symbol, does not interfere with information expressed in another, the orientation of a symbol. There are three basic high-level channels that match the areas shown in Figure 5.2—namely, color, form, and motion. We can use this fact to establish a basic principle of display design.

> **[G5.2]** Use different visual channels to display aspects of data so that they are visually distinct.

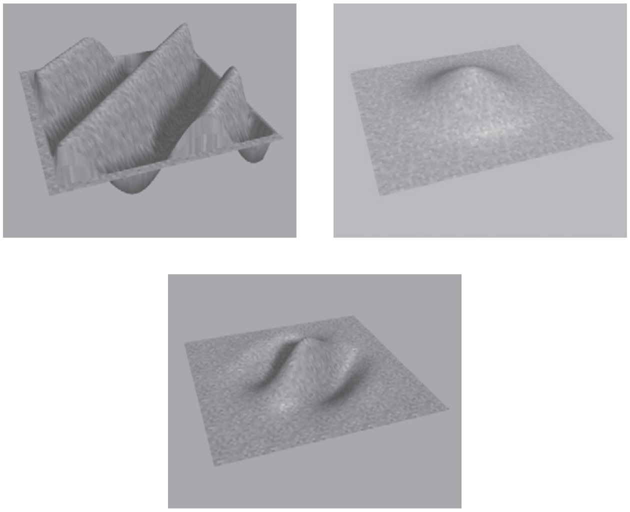


Figure 5.3 Gabor model of a V1 receptive field. Multiply the cosine wave grating on the upper left figure by the Gaussian envelope in the upper right figure to get the two-dimensional Gabor function shown on the bottom figure. The result is an excitatory center flanked by two inhibitory bars.

Once we understand the kinds of patterns the tuned cells of the visual cortex respond to best, we can apply this information to create efficient visual patterns. Patterns that can be separated based on the receptive field properties of V1 neurons should be rapidly found and easily distinguished. A number of assumptions are implicit in this account. They are worth critical examination.

One basic assumption is that the rate at which single neurons fire is the key coding variable in terms of human perception. This assumption can certainly be questioned (Montemurro et al., 2008). It may be that what is important is the way in which groups of neurons fire, or perhaps the temporal spacing or synchronization of cell firings. In fact, there is evidence that these alternative information codings are important, perhaps critical. Nevertheless, few doubt that neurons that are highly sensitive to color differences (in terms of their firing rates) are directly involved in the processing of color and that the same thing is true for motion and shape. Moreover, as we shall see, the behavior of neurons fits well with studies of how people perceive certain kinds of patterns.

Early-stage neurons are particularly important in determining how distinct things appear. We know that at higher levels of processing in the visual cortex, there are receptive fields that are much more complex; they respond to patterns that are composites of the simple receptive field patterns found at earlier stages. These more complex composite patterns, analyzed further up the visual processing chain, are not, in general, processed as rapidly.

The Gabor Model and Visual Distinctness

A number of electrophysiological and psychophysical experiments show that V1 and V2 contain large arrays of neurons that filter for orientation and size information at each point in the visual field. These neurons have both a preferred orientation and a preferred size (they are said to have spatial and orientation tuning). They are either weakly color coded or not color coded, responding to luminance patterns only.

A simple mathematical model used widely to describe the receptive field properties of these neurons is the Gabor function (Barlow, 1972; Daugman, 1984). The Gabor function has two components as illustrated in Figure 5.3: a cosine wave and a Gaussian envelope. Multiply them together, and the result is a function that responds strongly to bars and edges of a particular orientation and not at all to edges of a bar or edges at right angles to that orientation. Roughly, this can be thought of as a kind of fuzzy bar detector. It has a clear orientation, and it has an excitatory center, flanked by inhibitory bars. The opposite kind of neuron also exists, with an inhibitory center and an excitatory surround, as well as other variants.

Mathematically, a Gabor function has the following form (simplified for ease of explanation):

$$R = C \cos\left(\frac{Ox}{S}\right) \exp\left(-\frac{x^2 + y^2}{S}\right) \qquad (5.1)$$

The C parameter gives the amplitude or contrast value, S gives the overall size of the Gabor function by adjusting both the wavelength of the cosine grating and the rate of decay of the Gaussian envelope, and O is a rotation matrix that orients the cosine wave. Other parameters can be added to position the function at a particular location in space and adjust the ratio of the Gaussian size to the sine wavelength; however, orientation, size, and contrast are most significant in modeling human visual processing.

In an influential paper, Barlow (1972) developed a set of principles that have become influential in guiding our understanding of human perception. The second of these, called the "second dogma," provides an interesting theoretical background to the Gabor model. In the second dogma, Barlow asserted that the visual system is simultaneously optimized in both the spatial–location and spatial–frequency domains. Gabor detectors optimally preserve a combination of spatial information (the location of the information in visual space) and oriented-frequency information. A single Gabor detector can be thought of as being tuned to a little packet of orientation and size information that can be positioned anywhere in space. John Daugman (1984) showed mathematically that Gabor detectors satisfy the requirements of the Barlow dogma.

Many things about low-level perception can be explained by this model. Gabor-type detectors are used in theories of the detection of contours at the boundaries of objects (form perception), the detection of regions that have different visual textures, stereoscopic vision, and motion perception. The Gabor-type detector yields a basic set of properties out of which all more complex patterns are built. This stage of visual processing also determines some of the basic rules that make patterns distinctive at all subsequent levels of processing.

One thing that Gabor functions do is process parts of the image in terms of different spatial frequencies (see Chapter 2), and this has led to the concept of *spatial frequency channels*. These are subchannels of the form channel that encodes texture and the elements of shape. The halfwidth of the spatial tuning curve is approximately a period change (in the sinusoid) of a factor of 3, and the total number of spatial frequency channels is about 4. Wilson and Bergen (1979) determined these values using a masking technique, which essentially determines the extent to which one type of information interferes with another. The resulting estimation of spatial frequency channels is illustrated in Figure 5.4. The idea of spatial frequency channels, however, is different from the concept of separate channels made up of color, shape and texture or motion. It is more meaningful to think of spatial frequency channels as subchannels of the broader shape channel.

A single Gabor-type neuron is also broadly tuned with respect to orientation. Orientation tuning-in appears to be about 30 degrees (Blake & Holopigan, 1985); therefore, objects that differ from one another by more than 30 degrees in orientation will be more easily distinguished. Orientation can also be considered as a subchannel of form.

Probably none of the perceptual channels we shall discuss is fully independent; nevertheless, it is certainly the case that some kinds of information are processed in ways that are more independent than others. A channel that is independent from another is said to be orthogonal to it. Here, the concept is applied to the spatial information carried by Gabor detectors.

Because all information passes through spatial frequency channels, it is important to keep different kinds of information as separate as possible in terms of their frequency components and orientations.

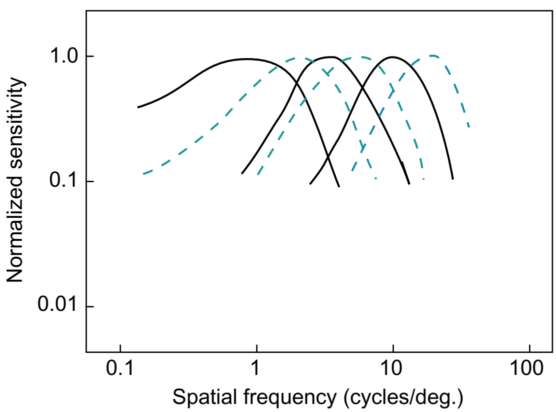


Figure 5.4 Wilson and Bergen (1979) spatial channels.

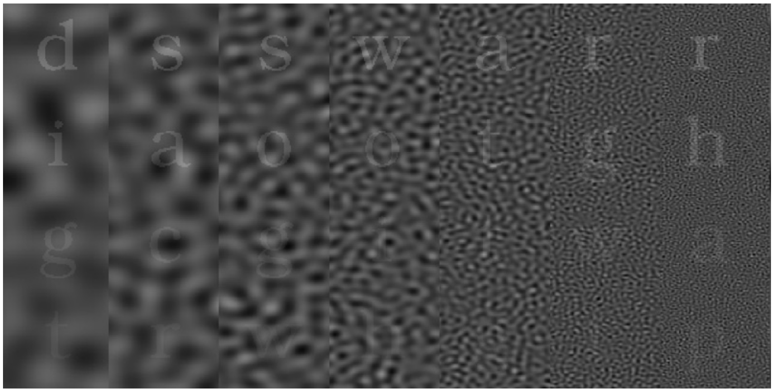


Figure 5.5 The letters are harder to see where they lie on top of visual noise that has spatial frequency components similar to the letters. (*From Solomon & Pelli (1994). Reproduced with permission.*)

Figure 5.5 shows the letters of the alphabet on top of a random visual noise pattern that has a range of spatial frequencies from low to high (Solomon & Pelli, 1994). As can be seen, the letters are difficult to perceive where the background has spatial frequency components similar to the letters. This is an example of visual interference between spatial frequency subchannels.

[G5.3] To make symbols easy to find, make them distinct from their background and from other symbols; for example, the primary spatial frequency of a symbol should be different from the spatial frequency of the background texture and from other symbols.

A Differencing Mechanism for Fine Discrimination

The very broad spatial and orientation tuning of Gabor-type detectors implies that we should not be able to discriminate small-sized orientation differences, yet this is clearly not the case. When people get enough time, they can resolve far smaller differences than they can with brief exposures. Given time, the resolvable size difference for a Gabor pattern is a size change of about 9% (Caelli & Bevan, 1983). The resolvable orientation difference is about 5 degrees (Caelli & Bevan, 1983). These resolutions are much smaller than the channel-tuning functions would predict. Neural differencing mechanisms can account for the higher resolution. The explanation for finer discriminations is *differencing mechanisms*, higher-level processes that sharpen up the output from individual receptors. The mechanism is based on inhibition. If a neuron has an excitatory input from one neuron and an inhibitory input from another with a slightly different tuning, the resulting difference signal is much more sensitive to spatial tuning than either of the original signals. This kind of sharpening is common

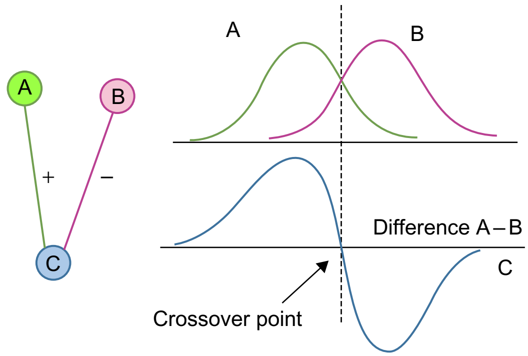


Figure 5.6 Differences between signals from neurons A and B are created by an excitatory and an inhibitory connection to neuron C.

in neural systems; it appears in color systems, edge detection, and size comparisons. Figure 5.6 illustrates the concept. Neurons A and B both have rather broadly tuned and somewhat overlapping response functions to some input pattern. Neuron C has an excitatory input from A and an inhibitory input from B. The result is that C is highly sensitive to differences between A and B at the crossover point.

The differencing mechanism explains why the visual system is exquisitely sensitive to differences, but not to absolute values. It also explains contrast effects because if one of the signals is rendered less sensitive, through lateral inhibition, the crossover point moves, but such fine discriminations are processed more slowly than the basic low-level responses. So, for rapid target finding, it is important that targets be distinct in orientation by 30 degrees or more and in size by a factor of two.

Feature Maps, Channels, and Lessons for Visual Search

To summarize to this point, because different kinds of visual properties are processed separately they can be thought of as forming separate feature maps, roughly at the V1 level. These maps cover the entire visual field, and there are many of them, each based on a different kind of feature. There is a map for redness, a map for greenness, a map for vertical orientation, a map for horizontal orientation, a map for motion, and so on.

When we are looking for something, a target set of feature properties is defined made up of the kinds of features that are found in feature maps (Eckstein et al., 2007). Eye movements are directed to feature map regions that best match the target properties. Figure 5.7 illustrates the idea. On the left is a set of symbols. On the right is how this image appears in a few of the feature maps. A search for red objects yields three candidate targets, and a search for black objects yields three different targets. A search for a left-slanted shape yields two strong and two weak targets. The oblique edges of the triangular symbols produce the weak signals, and these will somewhat distract in a search for the left-oriented bars.

Based on what we have learned so far, we can derive a number of lessons that can be applied to symbol set design. Low-level feature properties are critical.

[G5.4] Make symbols as distinct from each other as possible, in terms of both their spatial frequency components and their orientation components.

[G5.5] Make symbols as distinct as possible from background patterns in terms of both their spatial frequency components and their orientation components.

Figure 5.8 illustrates guideline G5.5 with a number of examples of scatterplots. The ones on the left use symbol shapes that are typical in many plotting packages.

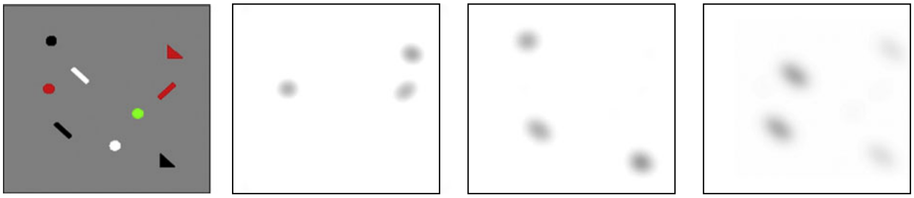


Figure 5.7 The symbols shown on the left are processed via a set of feature maps and the result directs eye movements.

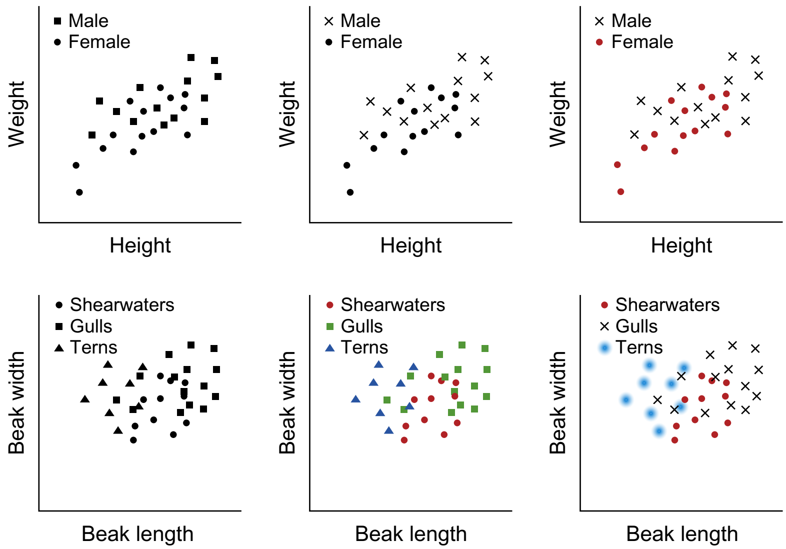


Figure 5.8 Feature channels can be used to make symbols more distinct from one another. The graphs on the right use redundant color coding in addition to more distinctive shapes.

The squares and circles are not very distinct because the differences are encoded in high spatial frequencies (see Figure 2.25 in Chapter 2, which shows how spatial sensitivity declines with high spatial frequencies). If the symbols were made larger they would be more distinct. The other examples in the center and the right have much more distinctive spatial subchannel components. Some use both color and form to increase separation in feature space.

Preattentive Processing and Ease of Search

Neuropsychology can only tell us so much about what makes shapes distinctive, because although the field is advancing rapidly the level of effort required for each discovery is huge. Inevitably, neuropsychological theory lags behind results from direct experiments using psychophysical methods with human observers. Psychophysics is the study of human responses to physically defined stimuli. There have been many experiments in which human observers are asked if a particular shape appears in a pattern of other shapes that are flashed briefly in front of their eyes. These studies have led to the concept of *preattentive processing* that is central to how we understand visual distinctiveness (Treisman, 1985).

Preattentive processing is best introduced with an example. To count the 3s in the table of digits shown in Figure 5.9(a), it is necessary to scan all the numbers sequentially. To count the 3s in Figure 5.9(b), it is necessary only to scan the red digits. This is because color is preattentively processed. Certain simple shapes or colors seem to pop out from their surroundings. The theoretical mechanism underlying popout was called *preattentive processing* because early researchers thought that it must occur prior to conscious attention, although a more modern view is that attention is integral, and we shall return to this point. In essence, preattentive processing determines what visual objects are offered up to our attention and easy to find in the next fixation

45929078059772098775972655665110049836645
27107462144654207079014738109743897010971
43907097349266847858715819048630901889074
25747072354745666142018774072849875310665

(a)

45929078059772098775972655665110049**3**6645
27107462144654207079014738109743897010971
4**3**907097**3**49266847858715819048630901889074
2574707**2**
(b)

Figure 5.9 Preattentive processing. (a) To count the 3s in this table of digits, it is necessary to scan the numbers sequentially. (b) To count the 3s in this table, it is only necessary to scan the red 3s because they pop out from their surroundings.

(Findlay & Gilchrist, 2005), so prior attention is part of the phenomenon. Still, although the term is misleading, we shall continue to use it because of its widespread adoption. In any case, the phenomena described by the term are very real and of critical importance.

A typical experiment conducted to find out whether some pattern is preattentively distinct involves measuring the response time to find a target among a set of other symbols called *distractors*—for example, finding the 3s in a set of other numbers. If processing is preattentive, the time taken to find the target should be equally fast no matter how many distracting nontargets there are. So, if time to find the target is plotted against number of distractors, the result should be a horizontal line. Figure 5.10 illustrates a typical pattern of results. The circles illustrate data from a visual target that is preattentively different from the distractors. The time taken to detect whether there is a red digit in the array of digits shown in Figure 5.9 is independent of the number of black digits. The Xs in Figure 5.10 show the results from processing a feature that is *not* preattentively distinct. In this case, time to respond *increases* with number of distractors suggesting sequential processing. The results of this kind of experiment are not always as perfectly clear cut as Figure 5.10 would suggest. Sometimes there is a small, but still measurable, slope in the case of a feature that is thought to be preattentive. As a rule of thumb, anything that is processed at a rate faster than 10 msec per item is considered to be preattentive. Typical processing rates for nonpreattentive targets are 40 msec per item and more (Treisman & Gormican, 1988).

Why is this important? In displaying information, it is often useful to be able to show things "at a glance." If you want people to be able to instantaneously identify some

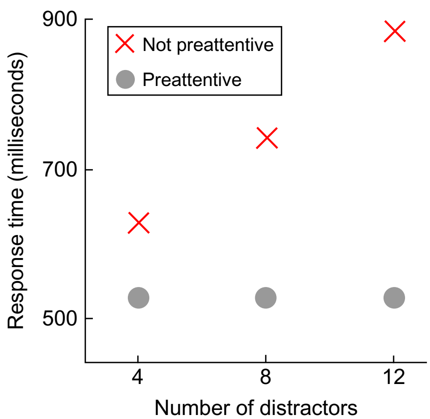


Figure 5.10 Typical results from a pattern of preattentive processing. The circles show time to perceive an object that is preattentively distinct from its surroundings. In this case, time to process is independent of the number of irrelevant objects (distractors). The Xs show how time to process nonpreattentively distinct targets increases with the number of distractors.

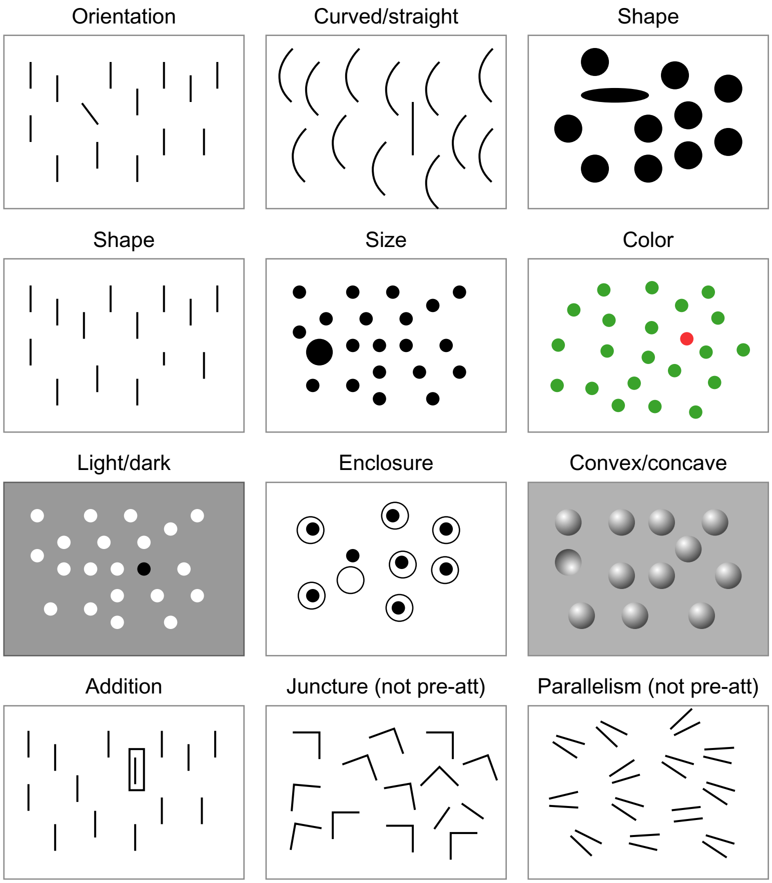


Figure 5.11 Most of the preattentive examples given here can be accounted for by the processing characteristics of neurons in the primary visual cortex.

mark on a map as being of type A, it should be differentiated from all other marks in a preattentive way. There have been literally hundreds of experiments to test whether various kinds of features are processed preattentively. Figure 5.11 illustrates a few of the results. Orientation, size, basic shape, convexity, concavity, and an added box around an object are all preattentively processed. However, the junction of two lines is not preattentively processed; neither is the parallelism of pairs of lines, so it is more difficult to find the targets in the last two boxes in Figure 5.11.

The features that are preattentively processed can be organized into a number of categories based on form, color, motion, and spatial position.

- Line orientation
- Line length
- Line width

- Size
- Curvature
- Spatial grouping
- Blur
- Added marks
- Numerosity (one, two, or three objects)
- Color
- Hue
    - Intensity
- Motion
    - Flicker
    - Direction of motion
- Spatial position
    - Two-dimensional position
    - Stereoscopic depth
- Convex/concave shape from shading

Originally, studying preattentive features was thought to be a way of measuring the primitives of early visual processing (Treisman & Gormican, 1988). The list given above, however, is considerably longer than the one that resulted from neuropsychological studies. Still, in most of these instances, the target is different from the surrounding nontargets in terms of the basic channels introduced earlier (color, size, contrast, orientation).

There is a risk of misinterpreting the findings of psychophysical studies and proposing a new kind of detector for every distinct shape. To take a single example, curved lines can be preattentively distinguished from straight lines. Despite this, it may be a mistake to think that there are curved line detectors in early vision. It may simply be the case that cells responsive to long, straight-line segments will not be strongly excited by the curved lines. Of course, it may actually be that early vision curvature detectors do exist; it is just that the evidence must be carefully weighed. It is not a good idea to propose a new class of detector for everything that exhibits the popout effect. The scientific principle of finding the most parsimonious explanation, known as Occam's razor, applies here.

It is also important to note that not all preattentive effects are equally strong. There are degrees of popout. In general the strongest effects are based on color, orientation, size, contrast, and motion or blinking, corresponding to the findings of neuropsychology. Effects such as line curvature tend to be weaker. Also, there are degrees of difference. Large color differences have more popout than small ones. Some popout effects occur with no instruction and are difficult to miss, such as the red 3s in Figure 5.9 and blinking points, but other patterns labeled preattentive require considerable attention for them to be seen. So the term *preattentive* should not be taken too literally because prior attention must be given to prime the relevant properties using the tuning mechanisms we have already discussed.

> **[G5.6]** Use strong preattentive cues before weak ones where ease of search is critical.

Attention and Expectations

A problem with most research into attention, according to a book by Arien Mack and Irvin Rock (1998), is that almost all perception experiments (except their own) demand attention in the very design. The authors have a point. Typically, a subject is paid to sit down and pay close attention to a display screen and to respond by pressing a key when some specified event occurs. This is not everyday life. Usually we pay very little attention to what goes on around us. To understand better how we see when we are not primed for an experiment, Mack and Rock conducted a laborious set of experiments that only required one observation from each experiment. They asked subjects to look at a cross for a fraction of a second and report when one of the arms changed length. So far, this is like most other perception studies, but the real test came when they flashed up something near the cross that the subjects had *not* been told to expect. Subjects rarely saw this unexpected pattern, even though it was very close to the cross they were attending to in the display. Mack and Rock could only do this experiment once per subject, because as soon as subjects were asked if they had seen the new pattern they would have started looking for "unexpected" patterns. Hundreds of subjects had to be used, but the results were worth it; they tell us how much we are likely to see when we are looking for something else. The answer is, not much.

The fact that most subjects did not see a wide range of unexpected targets tells us that humans do not perceive much unless we have a need to find something and a vague idea of what that something looks like. In most systems, brief, unexpected events will be missed. Mack and Rock initially claimed from their results that there is no perception without attention; however, because they found that subjects generally noticed larger objects, they were forced to abandon this extreme position.

The question of which visual dimensions are preattentively stronger and therefore more salient cannot be answered in a simple way, because it always depends on the strength of the particular feature and the context. For example, Callaghan (1989) compared color to orientation as a preattentive cue. The results showed that the preattentiveness of the color

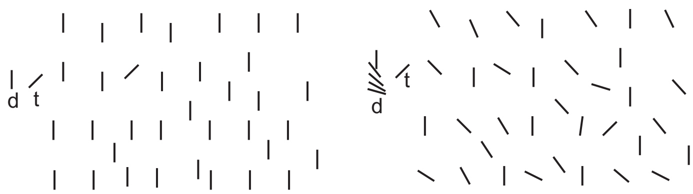


Figure 5.12 On the left, the right-slanted bar pops out; on the right, it does not. Yet, most of the distractors on the right have an orientation that is more different from the target orientation than the distracters on the left.

depended on the saturation (vividness) and size of the color patch, as well as the degree of difference from surrounding colors. So it is not just a question of color versus orientation, but exactly how the color differs from other colors in the set. Similarly, the preattentiveness of line orientation depends on the length of the line, the degree to which it differs from surrounding lines, and the contrast of the line pattern with the background. Figure 5.12 shows how an oblique line stands out from a set of vertical lines. When the same oblique line is in a set of lines of various orientations it is much more difficult to see, even though the difference in orientation between the target and the distractor set is just as large or larger. One thing that is clear from this example is that preattentive symbols become less distinct as the variety of distractors increases. It is easy to spot a single hawk in a sky full of pigeons, mostly because it has a different motion pattern, but if the sky contains a greater variety of birds, the hawk will be more difficult to see.

Studies have shown that two factors are important in determining whether something stands out preattentively: the degree of difference of the target from the nontargets and the degree of difference of the nontargets from each other (Quinlan & Humphreys, 1987; Duncan & Humphreys, 1989). For example, yellow highlighting of text works well if yellow is the only color in the display besides black and white, but if there are many colors the highlighting will be less effective.

> **[G5.7]** For maximum popout, a symbol should be the only object in a display that is distinctive on a particular feature channel; for example, it might be the only item that is colored in a display where everything else is black and white.

Highlighting and Asymmetries

Another issue relating to making targets distinctive comes from research that has revealed *asymmetries* in some preattentive factors; for example, *adding* marks to highlight a symbol is generally better than taking them away (Treisman & Gormican, 1988). If all of the symbols in a set except for a target object have an added mark, the target will be less distinctive. It is better to highlight a word by underlining it than to underline all the words in a paragraph except for the target word. Another asymmetry

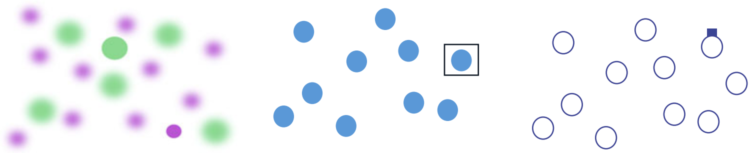


Figure 5.13 A number of highlighting methods that use positive asymmetric preattentive cues: sharpness, added surrounding feature, added shape.

is the finding that a big target is easier to see surrounded by small targets than a small target surrounded by big targets. Several examples are given in Figure 5.13.

> **[G5.8]** Use positively asymmetric preattentive cues for highlighting.

When a visual design is complex, employing color, texture, and shape, the highlighting problem becomes more difficult. If all of the fonts in a display have the same size, for example, an increase in size can be used for highlighting.

> **[G5.9]** For highlighting, use whatever feature dimension is used least in other parts of the design.

Modern computer graphics permit the use of motion for highlighting. This can be very effective when there is little other motion in the display (Bartram & Ware, 2002; Ware & Bobrow, 2004); however, making things move may be too strong a cue for many applications, although quite subtle motion can be effective.

> **[G5.10]** When color and shape channels are already fully utilized, consider using motion or blink highlighting. Make the motion or blinking as subtle as possible, consistent with rapid visual search.

A relatively new idea for highlighting is the use of blur. Kosara et al. (2002) suggested blurring everything else in the display to make certain information stand out. They call the technique *semantic depth of field*, because it applies the depth-of-focus effects that can be found in photography to the display of data according to semantic content. As Figure 5.13 illustrates, blur works well, although again there is an obvious potential drawback to the technique. By blurring, the designer runs the risk of making important information illegible, as it is usually not possible to reliably predict the interests of the viewer.

Coding with Combinations of Features

So far we have been concentrating on using a single visual channel to make symbols distinct, or to highlight; often, though, we may wish to make objects distinctive using two or more channels. There are two issues here. The first is using redundant coding for extra distinctiveness. The second is, what can we expect if we use more complex patterns in symbol design?

Coding with Redundant Properties

We can choose to make something distinct on a single feature dimension, such as color, or we can choose to make it distinct on several dimensions, such as color, size, and orientation. This is called *redundant coding*. It means that someone can search based on any or all of the properties. The degree to which search is improved by redundant coding is a complex issue; sometimes the benefit is a simple addition and sometimes it is less than additive. It depends on what visual properties are being employed and the background. Nevertheless, there is almost always a benefit to redundant coding (Eriksen & Hake, 1955; Egeth & Pachella, 1969). Figure 5.8 gives examples of redundant coding of symbols in scatterplots.

> **[G5.11]** To make symbols in a set maximally distinctive, use redundant coding wherever possible; for example, make symbols differ in both shape and color.

What Is Not Easily Findable: Conjunctions of Features

So far we have been discussing what can easily be found, but what kinds of things are difficult to spot? The answer is that, even if visual patterns get just a little bit more complex, a search can change from being almost instantaneous to something requiring much longer serial processing. What happens, for example, if we wish to search for a red square, not just something that is red or something that is square? Figure 5.14 illustrates a conjunction search task in which the targets are three red squares. It turns out that this kind of search is slow if the surrounding objects are squares (but not red ones) and other red shapes. We are forced to do a serial search of *either* the red shapes or the square objects. This is called a *conjunction* search, because it involves searching

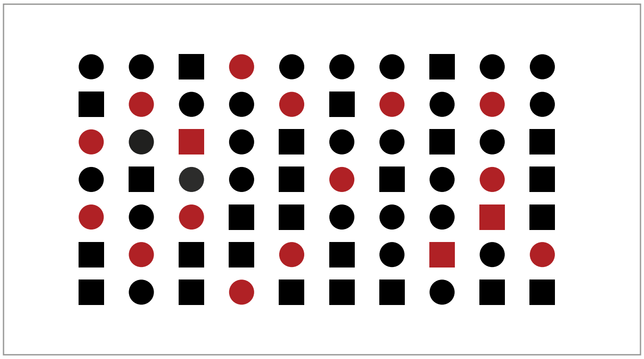


Figure 5.14 Searching for the red squares is slow because they are identified by a conjunction of shape and color.

for the specific conjunction of redness *and* shape attributes (Treisman & Gelade, 1980). This is very different from redundant coding, where parallel search can be carried out on one *or* the other. Conjunction searches are generally not preattentive, although there are a few very interesting exceptions that we will get to shortly.

The fact that conjunction searches are slow has broad implications. It means, among other things, that we cannot learn to rapidly find more complex patterns. Even though we may have hundreds or thousands of hours of experience with a particular symbol set, searching for conjunctions of properties is still slow, although a modest speedup is possible (Treisman et al., 1992).

> **[G5.12]** If symbols are to be preattentively distinct, avoid coding that uses conjunctions of basic graphical properties.

Highlighting Two Data Dimensions: Conjunctions That Can Be Seen

Although early research suggested that conjunction searches were never preattentive, it has emerged that there are a number of preattentive dimension pairs that do allow for conjunctive search. Interestingly, these exceptions are all related to space perception. Searches can be preattentive when there is a conjunction of spatially coded information and a second attribute, such as color or shape. The spatial information can be a position on the *XY* plane, stereoscopic depth, shape from shading, or motion.

Spatial grouping on the *XY* plane. Treisman and Gormican (1988) argued that preattentive search can be guided by the identification of spatial clusters. This led to the discovery that the conjunction of space and color can be searched preattentively. In Figure 5.15(a), we cannot conjunctively search for green ellipses, but in Figure 5.15(b), we can rapidly search the conjunction of lower cluster and green target.

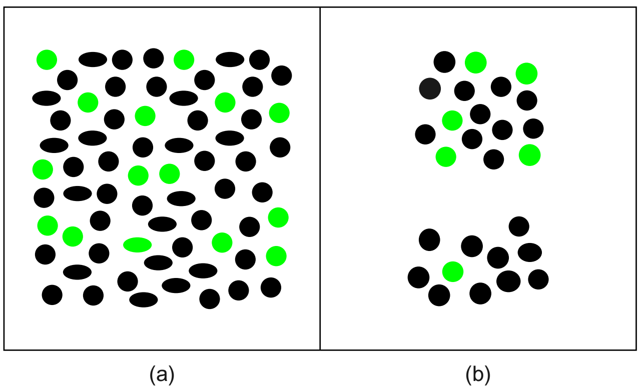


Figure 5.15 (a) With the conjunction of shape and color, search is slow. (b) If we search the lower group for the green object, the search is fast. This is also a conjunction.

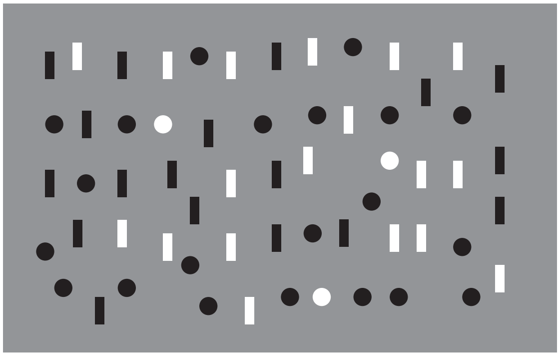


Figure 5.16 The white circles are a conjunction of shape and luminance polarity; nevertheless, they can be found preattentively.

Stereoscopic depth. Nakayama and Silverman (1986) showed that the conjunction of stereoscopic depth and color, or of stereoscopic depth and movement, can be preattentively processed.

Luminance polarity and shape. Theeuwes and Kooi (1994) showed that luminance polarity with targets lighter and darker than a gray background can support a preattentive conjunction search. In Figure 5.16, the white circles can be searched in parallel (a conjunction of whiteness and shape).

Convexity, concavity, and color. D'Zmura et al. (1997) showed that the conjunction of perceived convexity and color can be preattentively processed. In this case, the convexity is perceived through shape-from-shading information.

Motion. Driver et al. (1992) determined that motion and target shape can be preattentively scanned conjunctively. Thus, if the whole set of targets is moving, we do not need to look for nonmoving targets. We can preattentively find, for example, the red moving target. This may be very useful in producing highlighting techniques that allow for a preattentive search within the set of highlighted items (Bartram & Ware, 2002; Ware & Bobrow, 2004).

An application in which preattentive spatial conjunction may be useful is found in geographic information systems (GISs). In these systems, data is often characterized as a set of layers—for example, a layer representing the surface topography, a layer representing minerals, and a layer representing ownership patterns. Such layers may be differentiated by means of motion or stereoscopic depth cues.

[G5.13] When it is important to highlight two distinct attributes of a set of entities, consider coding one using motion or spacial grouping and the other using a property such as color or shape.

Ware and Bobrow (2005) used a conjunction coding method in an interactive network visualization application. To make it possible to trace paths in a visually impenetrable mass of hundreds of nodes and links, we added a feature whereby when someone touched a node a subnetwork of closely linked nodes and edges jiggled by a small amount (motion coding). This made the subnetwork stand out strongly from the background information. Previously found subnetworks were highlighted in a more conventional way using color coding. We found that it was easy for people to focus either on the recently selected subnetwork or on the previously selected subnetwork or on a sub-subnetwork that was both recently and previously selected (a conjunction).

Integral and Separable Dimensions: Glyph Design

Another body of theory that is relevant to glyph design is the theory of *integral and separable dimensions*, developed by Garner (1974). The kind of multidimensional coding that occurs in the use of glyphs raises questions about the perceptual independence of the display dimensions. In many ways, the lessons are the same as from channel theory (visual dimensions are much the same as channels), but Garner's theory provides a useful alternative description. We will use it to discuss approaches to glyph design.

Sometimes we need a symbol to do more than simply stand for something. Sometimes it is useful if symbols can convey how large, hot, or wet something is. Figure 5.17 shows an example in which the size of each circle represents the population of a country, and the color represents the geographic region to which that country belongs. In

Figure 5.17 In this visualization, the color of each circle represents a geographic region and the size of the circle represents population. (*From www.gapminder.org.*)

this case, color functions as a nominal coding, whereas size represents a quantity, a ratio coding. Symbols that represent quantity are called *glyphs*. To create a glyph, one or more quantitative data attributes are mapped in a systematic way to the different graphical properties of an object.

Garner's theory helps us answer questions such as, "Will the color-coding scheme interfere with our perception of glyph size and therefore distort perceived population level?" or "What if we use both color and size to represent a single variable—will this make the information clearer?" The concept of integral vs. separable visual dimensions tells us when one display attribute (e.g., color) will be perceived independently from another (e.g., size).

With *integral display dimensions*, two or more attributes of a visual object are perceived holistically and not independently. An example is a rectangular shape, perceived as a holistic combination of the rectangle's width and height. Another is the combination of green light and red light; this is seen holistically as yellow light, and it is difficult to respond independently to the red and green components.

With *separable dimensions*, people tend to make separate judgments about each graphical dimension. This is sometimes called *analytic processing*. Thus, if the display dimensions are the diameter of a ball and the color of a ball, they will be processed relatively independently. It is easy to respond independently to ball size and ball color. Integral and separable dimensions have been determined experimentally in a number of ways.

Three experimental paradigms are discussed here. All are related to interactions between pairs of graphical qualities, such as size and color. Very little work has been done on interactions among three or more graphical qualities.

Restricted Classification Tasks

In restricted classification tasks, observers are shown sets of three glyphs that are constructed according to the diagram shown in Figure 5.18. Two of the glyphs (A and B) are made the same on one graphical feature dimension. A third glyph (C) is constructed so that it is closer to glyph B in feature space, but this glyph differs from the other two in both of the graphical dimensions. Subjects are asked to group the two glyphs that they think go together best. If the dimensions are integral, B and C are grouped together because they are closest in the feature space. If they are separable, A and B are grouped together because they are identical in one of the dimensions (analytic mode). The clearest example of integral dimensions is color space dimensions. If dimension X is the red–green dimension and dimension Y is the yellow–blue dimension of color space, subjects tend to classify objects (roughly) according to the Euclidean distance between the colors (defined according to one of the uniform color spaces discussed in Chapter 4). Note that even this is not always the case, as the evidence of color categories (also discussed in Chapter 4) shows.

The width and height of an ellipse create an integral perception of shape. Thus, in Figure 5.19(a, top) the ellipses appear to be more similar to each other than to the circle, even though the width of the circle matches the width of the first ellipse. If

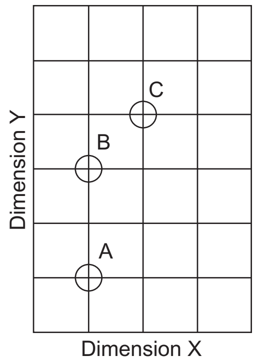


Figure 5.18 It is useful to think in terms of two display dimensions when considering the integral–separable concept. One dimension might be color, while another might be some aspect of shape.

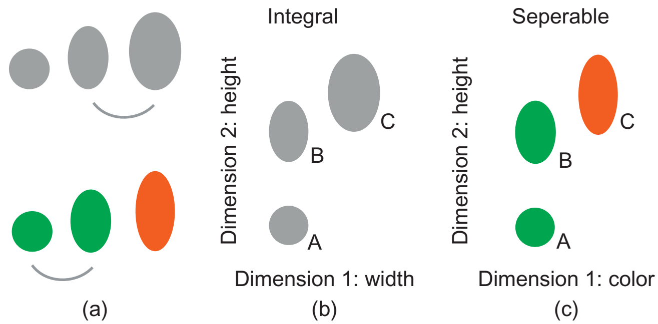
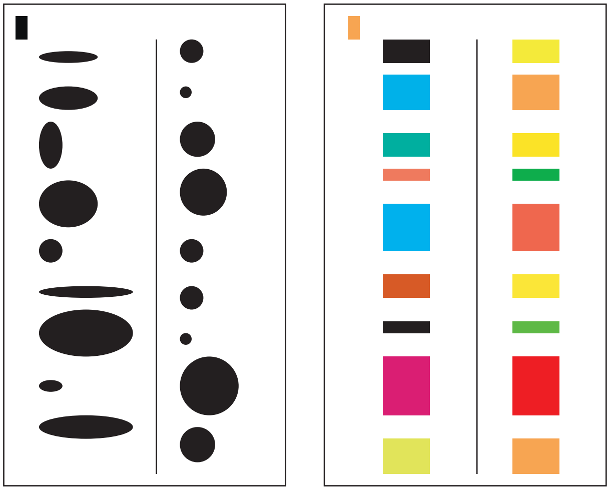


Figure 5.19 (a) The width and height of an ellipse are perceived integrally, so the ellipses are seen as more similar to each other (because they have the same shape) than the pair having the same width. The color and height of a shape are perceived separably, so the two green shapes are seen as most similar. (b, c) Space plots of the two examples.

the two dimensions are separable, subjects act in a more analytic manner and react to the fact that two of the objects are actually identical on one of the dimensions. Shape and color are separable. Thus, in Figure 5.19(a, below) either the green shapes or the two elliptical shapes will be categorized together. With separable dimensions, it is easy to attend to one dimension or the other.

Speeded Classification Tasks

Speeded classification tasks tell us how glyphs can visually interfere with each other. In a speeded classification task, subjects are asked to quickly classify visual patterns according to only one of the visual attributes of a glyph. The other visual attribute can be set up in two different ways; it can be given random values (interference condition), or it can be coded in the same way as the first dimension (redundant coding). If the data dimensions are integral, substantial interference occurs in the first case. With redundant coding, classification is generally speeded for integral dimensions. With separable codes, the results are different. There is little interference from the



(a) (b)

Figure 5.20 Sets of patterns for a speeded classification task. In both cases, (a) and (b), participants are required to respond positively to only those glyphs that have the same *height* as the bar in the upper corner. The interference condition is on the left in both (a) and (b). (a, left) The variable widths interfere with classification based on height. (b, left) The variable color does not interfere with classification based on height. (a, right) Redundant size coding speeds classification. (b, right) Redundant color and size coding does not speed classification.

irrelevant graphical dimension, but there is also little advantage in terms of speeded classification when redundant coding is used. Of course, in some cases, using redundant separable codes may still be desirable; for example, if both color and shape are used for information coding, color-blind individuals will still have access to the information. Figure 5.20 gives examples of the kinds of patterns that are used in integral–separable dimension experiments, illustrating these points.

The lessons to be learned from integral–separable dimension experiments are easy to apply in cases in which each data entity has only two attributes.

> **[G5.14]** If it is important for people to respond holistically to a combination of two variables in a set of glyphs, map the variables to integral glyph properties.

> **[G5.15]** If it is important for people to respond analytically to a combination of variables, making separate judgments on the basis of one variable or the other, map the variables to integral glyph properties.

Figure 5.21 shows how integral dimensions can help us perceive the combination of two variables. The body mass index is a common measure of obesity. This index is a ratio of height squared to weight. If we use two integral values, ellipse height and ellipse width, to show height squared and weight respectively, then we can arrange the plot in such a way that the ideal height-to-weight relationship is a perfect circle. Someone who is overweight will be represented as a squashed ellipse, while someone who is very thin will be represented by a tall ellipse. On the left side of Figure 5.21, we can see at a glance who is overweight and who is underweight.

The right-hand side of Figure 5.21 shows the same data represented using two separable variables: red–green variation for weight and vertical size for height. This is a poor choice, as it is very difficult to see who is overweight and who is underweight.

We can also apply the lessons of integral and separable dimensions to data glyphs designed to represent many variables. Figure 5.22 shows a field of data glyphs from Kindlmann and Westin (2006) in which three variables are mapped to color and many more are mapped to the shape of the glyphs. Detailed knowledge of the application would be required to decide if this is a good representation, but this is not our concern

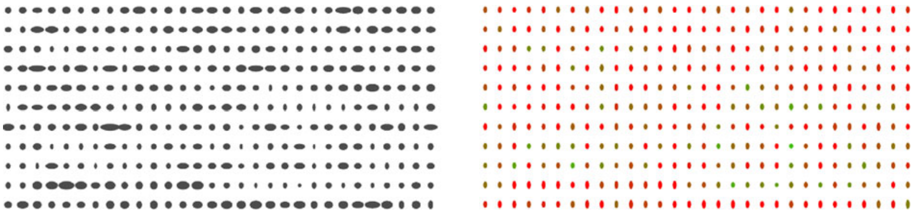


Figure 5.21 Height and weight data from 400 elderly Dutch people is displayed. On the left, height squared is mapped to the height of each ellipse and the weight is mapped to the width. On the right, weight is mapped to color and the width is held constant (red is more, green is less).

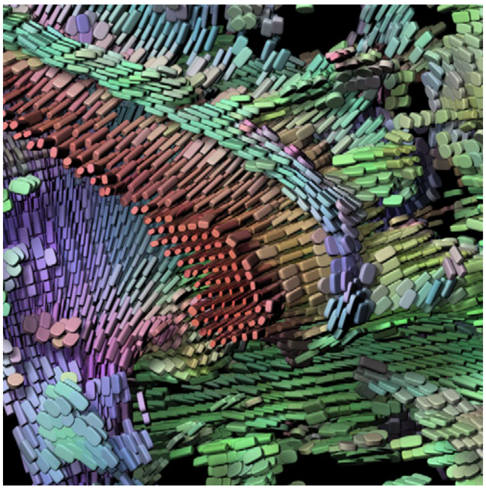


Figure 5.22 This map of a tensor field from Kindlmann and Westin (2006) has some variables mapped to the color of the lozenge-like glyphs and some variables mapped to their shape and orientation.

here. The point of showing it is to illustrate how the color-mapped variables tend to be seen integrally and independently (separably) from the shape variables, which also tend to be viewed holistically, making up the lozenge shapes.

Integral–Separable Dimension Pairs

The preceding analysis presented integral and separable dimensions as if they were qualitatively distinct. This overstates the case; a continuum of integrality–separability more accurately represents the facts. Even between the most separable dimension pairs, there is always some interference between different data values presented using the different channels. Likewise, the most integral dimension pairs can be regarded analytically to some extent. We can, for example, perceive the degree of redness and the degree of yellowness of a color—for example, orange or pink. Indeed, the original experimental evidence for opponent color channels was based on analytic judgments of exactly this type (Hurvich, 1981).

Figure 5.23 provides a list of display dimension pairs arranged on an integral–separable continuum. At the top are the most integral dimensions. At the bottom are

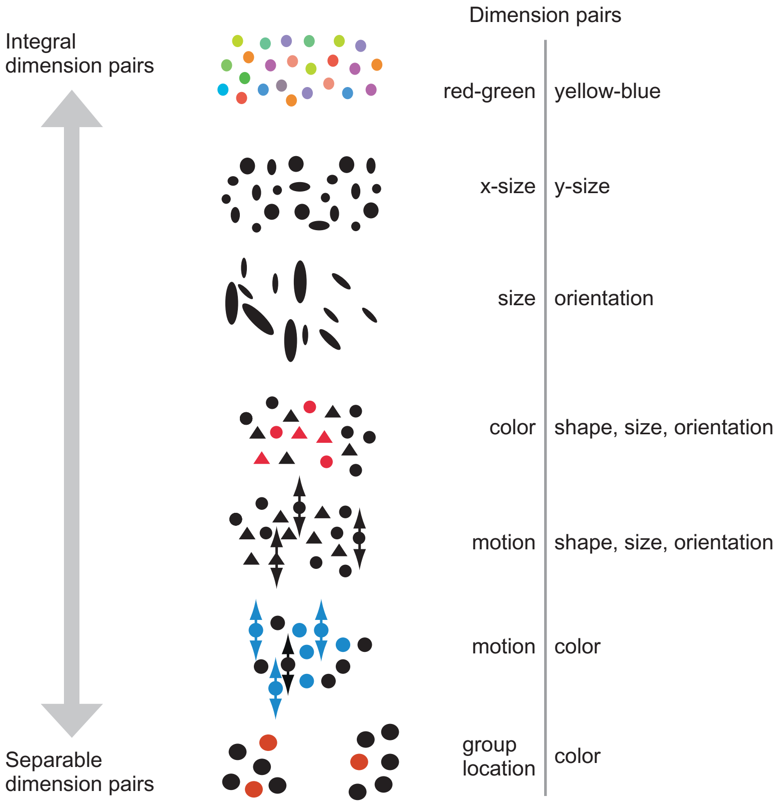


Figure 5.23 Examples of glyphs coded according to two display attributes. At the top are more integral coding pairs. At the bottom are more separable coding pairs.

the most separable dimensions. Some display dimensions are not represented in Figure 5.23 because of too little evidence. For example, one method of separating values is to use stereoscopic depth. It seems likely that stereoscopic depth is quite separable from other dimensions, especially if only two depth layers are involved.

As a theoretical concept, the notion of integral and separable dimensions is undoubtedly simplistic; it lacks mechanism and fails to account for a large number of exceptions and asymmetries that have been discovered experimentally. Also, it says essentially the same thing as channel theory, and channel theory has a firm neuropsychological basis. The beauty of the integral–separable distinction lies in its simplicity as a design guideline.

Representing Quantity

Some visual qualities increase continuously, such as size, brightness, or height above the ground, and are said to be monotonic. Some visual qualities are not monotonic. Orientation is one. It is meaningless to say that one orientation is greater or less than another. The same is true of the phase angle between two oscillating objects. As the phase difference is increased, the objects first appear to move in opposite directions, but as the phase difference continues to increase, they appear to move together again. Phase is cyclic, just as line orientation is cyclic. Hue also lacks a natural order.

Monotonic display variables naturally express relations, such as greater than or less than, if they have a quality that we associate with increasing value. For example, in a three-dimensional data space, the up direction is defined by gravity, and using up to represent a greater quantity of some variable will be readily interpreted, but the left and right directions do not have as clear a value. In the West, we read left to right but this is learned. Other languages, such as Arabic, have right-to-left ordering.

> **[G5.16]** When designing a set of glyphs to represent quantity, mapping to any of the following glyph attributes will be effective: size, lightness (on a dark background), darkness (on a light background), vividness (higher saturation) of color, or vertical position in the display.

If we map a data variable to some visual attribute such as length, area, volume, or lightness, we should be able to judge relative quantities at a glance, although not very accurately. Because of the simultaneous contrast effects discussed previously, grayscales are particularly subject to error. Judged length and area are also subject to contrast effects, although these will be smaller. Length will generally be judged more accurately than area, particularly if people are required to judge the relative area of different shapes (Cleveland & McGill, 1984). Perceived volume is judged very poorly, as shown in a study by Ekman and Junge (1961), who found perceived volume to be

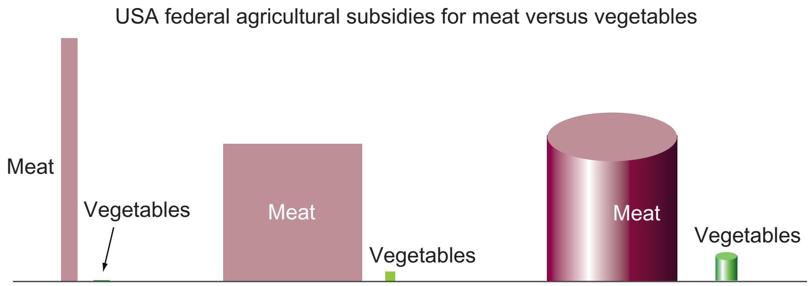


Figure 5.24 The same information is shown using length, area, and volume. Research shows that the quantities shown in the volume display on the right will be mostly judged according to the relative area of the images, not according to volume, resulting in large errors.

proportional to the actual volume raised to a power of 0.75. Because this is close to the relationship between volume and area, they concluded subjects were actually using area rather than volume for their judgments. The advantage to using area over length is that area is capable of conveying larger variations; for example, a 1-mm square can be compared to a 1-cm square, giving a ratio of 100:1. If length were used instead and the larger quantity were represented by 2 cm, then the smaller quantity would have to be represented by a length of only 0.2 mm, something barely visible. Figure 5.24 illustrates this point with data representing U.S. federal subsidies for meat and vegetables. Area representation is useful when relative amounts vary greatly.

> **[G5.17]** Ideally, use glyph length or height, or vertical position, to represent quantity. If the range of values is large, consider using glyph area as an alternative. Never use the volume of a three-dimensional glyph to represent quantity.

Mathematicians and engineers use the logarithmic plot in cases where there is a large variation in magnitude, but this is not a perceptual solution, relying instead on a technical understanding of the effects of the logarithmic transformation.

Representing Absolute Quantities

Visualization is mostly about seeing patterns in data, and this means that seeing if a particular variable is relatively larger or smaller than another is what is critical, rather than reading an absolute quantity. This is a good thing because the kinds of representation we have been discussing do not work well for representing quantities. Generally, only three to five distinct values can be reliably read using simple graphical variables such as color, size, or lightness. This means that glyphs using simple mappings are unsuitable for presenting data where values must be read from a display.

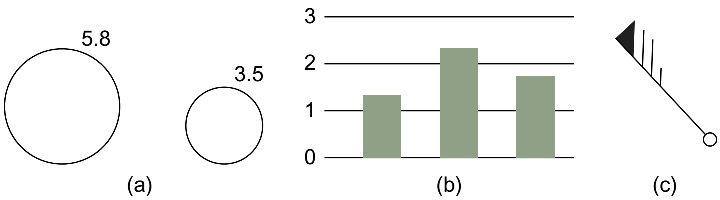


Figure 5.25 Three different ways that more exact numerical values can be read from a diagram.

There are a number of solutions to the problem of representing quantities. One is simply to add numbers to a glyph, or a numerical scale; see Figure 5.25(a, b). But, unless it is done carefully, the numbers will add visual noise, obscuring important patterns in data. A second solution is to create a glyph that by its shape conveys numerical values. The best known example of this is the wind barb, which is shown in Figure 5.25(c). A wind barb is a glyph widely used in meteorology that is a kind of hybrid of perceptual features and symbolic features. The shaft of the barb represents the direction of the wind. The "feathers" of the barb encode wind speed, so that someone familiar with the code can read off the wind speed to an accuracy of 5 knots. Given that surface wind speeds range up to about 150 knots, this means that wind barbs have about 30 steps of resolution, far better than any simple variation in size or color. The wind barb, however, has perceptual problems. The barb feathers greatly interfere with the perception of wind direction and because of this wind barbs are very poor at showing patterns in the winds.

Multidimensional Discrete Data: Uniform Representation versus Multiple Channels

This is a good place to step back and look at the general problem of multivariate discrete data display in light of the concepts that have been presented here and in previous chapters. It is worth restating this problem. We are provided with a set of entities, each of which has values on a number of attribute dimensions. For example, we might have 1000 beetles, each measured on 30 anatomical characteristics, or 500 stocks, each described by 20 financial variables. The reason for displaying such data graphically is often data exploration—to find meaning in the diversity. In the case of the beetles, the meaning might be related to their ecological niche. In the case of the stocks, the meaning is likely to lie in opportunities for profit. In either case, we are likely to be interested in patterns in the data, such as clusters of beetles that share similar attribute values.

If we decide to use a glyph display, each entity becomes a graphical object and data attributes are mapped to graphical attributes of each glyph. The problem is one of mapping data dimensions to the graphical attributes of the glyph. The work on preattentive processing, early visual processing, and integral and separable dimensions

Table 5.1 *Graphical attributes that may be useful in glyph design.*

Visual Variable	Dimensionality	Comment
Spatial position	Three dimensions: *X*, *Y*, *Z*	
Color	Three dimensions: defined by color opponent theory	Luminance contrast is needed to specify all other graphical attributes.
Shape	Size and orientation are basic but there may be more usable dimensions	The dimensions of shape that can be rapidly processed are unknown; however, the number is certainly small.
Surface texture	Three dimensions: orientation, size, and contrast	Surface texture is not independent of shape or orientation; uses one color dimension.
Motion coding	Approximately two to three dimensions; more research is needed, but phase is critical	
Blink coding	One dimension	Motion and blink coding are highly interdependent.

suggests that a rather limited set of visual attributes is available to us if we want to understand the values rapidly. Table 5.1 lists the most useful low-level graphical attributes that can be applied to glyph design, with a few summary comments about the number of dimensions available.

Many of these display dimensions are not independent of one another. To display texture, we must use at least one color dimension (luminance) to make the texture visible. Blink coding will certainly interfere with motion coding. Overall, we will probably be fortunate to display eight types of dimensional data clearly, using color, shape, spatial position, and motion to create the most differentiated set possible.

There is also the issue of how many resolvable steps are available in each dimension. The number here is also small. When we require rapid preattentive processing, only a handful of colors are available. The number of orientation steps that we can easily distinguish is probably about four. The number of size steps that we can easily distinguish is no more than four, and the values for the other data dimensions are also in the single-digit range. It is reasonable, therefore, to propose that we can represent about 2 bits of information for each of the eight graphical dimensions. If the dimensions were truly independent, this would yield 16 displayable bits per glyph (64,000 values). Unfortunately, conjunctions are generally not preattentive. If we allow no conjunction searching, we are left with four alternatives on each of eight dimensions, yielding only 32 rapidly distinguishable alternatives, a far smaller number. Anyone who has tried to design a set of easily distinguishable glyphs will recognize this number to be more plausible.

There is also the issue of the semantics associated with design choices, such as whether to use color or size to represent a particular attribute. Temperature, for example, has a natural mapping to color because of the association of redness with greater heat and blueness to lesser heat. Using the size of a glyph to represent temperature would normally be a poor design choice; however, there is a natural mapping between an increase in the amount of some variable and vertical size, or height above a baseline (Pinker, 2007). Orientation information, such as the direction of flow in a vector field is best represented by the orientation of a glyph—if a glyph representation is chosen, using color to represent orientation would normally be a poor design choice.

> **[G5.18]** In general, the use of heterogeneous display channels is best combined with meaningful mappings between data attributes and graphical features of a set of glyphs.

Stars and Whiskers

Sometimes no natural mappings to channels exist and it is desirable that there be a more symmetric mapping of data dimensions to the visual properties of a glyph. In this case, bar charts and star and whisker plots can be considered.

In the whisker plot, each data value is represented by a line segment radiating out from a central point, as shown in Figure 5.26(a). The length of the line segment denotes the value of the corresponding data attribute. A variant of the whisker plot is the star plot (Chambers et al., 1983). This is the same as the whisker plot but with the ends of the lines connected, as in Figure 5.26(b). It is possible to show a large number of variables with whisker or star plots, but this does not mean that the results will be intelligible. If there are a large number of whisker glyphs in a display, there will be visual interference between all contours having a similar orientation, with the star plot being the worst in this regard. In order to minimize interference between similarly oriented contours, a much smaller number of whiskers is recommended—four is probably the maximum. It may also be useful to change the amount of "energy" in glyph segments by

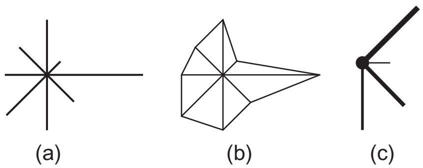


Figure 5.26 (a) Whisker plot. (b) Star plot. (c) Whisker plot with only four variables and varying width.

altering the line width as well as the length of the line; see Figure 5.26(c). A more common alternative to star and whisker plots is small bar charts, such as miniature versions of Figure 5.25(b). These have the advantage that orientation does not have to be taken into account in judging the represented quantities, and the bars can be color coded to make it easier to distinguish the variables.

When the data has many dimensions, a much better tool for its analysis is the parallel coordinates plot discussed in later chapters. This uses interactivity to minimize interference between dimensions.

The Searchlight Metaphor and Cortical Magnification

We now return to the topic of visual search with which we began this chapter. Consider the eyeball as an information-gathering searchlight, sweeping the visual world under the guidance of the cognitive centers that control our attention. Information is acquired in bursts, a snapshot for each fixation. More complex, nonpreattentive objects are scanned in series, one after another, at about the rate of 40 items per second. This means that we can typically parse somewhere between three and six items before the eye jumps to another fixation.

Useful Field of View

The attention process is concentrated around the fovea, where vision is most detailed; however, we can to some extent redirect attention to objects away from the fovea. The region of visual space we attend to expands and contracts based on task, the information in the display, and the level of stress in the observer. A metaphor for the fovea-centered attentional field is the *searchlight of attention*. When we are reading fine print, the searchlight beam is the size of the fovea, perhaps one centimeter from the point of fixation. If we are looking at a larger pattern, the searchlight beam expands. A concept called the *useful field of view* (UFOV) has been developed to define the size of the region from which we can quickly take in information. The UFOV varies greatly, depending on the task and the information being displayed. Experiments using displays densely populated with targets reveal small UFOVs, from 1 to 4 degrees of visual angle (Wickens, 1992). Drury and Clement (1978), however, have shown that for low target densities (less than one per degree of visual angle) the UFOV can be as large as 15 degrees. Roughly, the UFOV varies with target density to maintain a constant number of targets in the attended region. With greater target density, the UFOV becomes smaller and attention is more narrowly focused; with a low target density, a larger area can be attended.

Tunnel Vision, Stress, and Cognitive Load

A phenomenon known as *tunnel vision* has been associated with operators working under extreme stress. In tunnel vision, the UFOV is narrowed so that only the most important information, normally at the center of the field of view, is processed. This phenomenon has been specifically associated with various kinds of nonfunctional behaviors that occur during decision making in disaster situations. The effect can be demonstrated quite simply. Williams (1985) compared performance on a task that required intense concentration (high foveal load) to one that was simpler. The high-load task involved naming a letter drawn from six alternatives; the low-load task involved naming a letter drawn from two alternatives. They found a dramatic drop in detection rate for objects in the periphery of the visual field (down from 75% correct to 36% correct) as the task load increased. The Williams data shows that we should not think of tunnel vision strictly as a response to disaster. It may generally be the case that as cognitive load goes up, the UFOV shrinks.

> **[G5.19]** When designing user interrupts, peripheral alerting cues must be made stronger if the cognitive load is expected to be high.

The Role of Motion in Attracting Attention

A study by Peterson and Dugas (1972) suggests that the UFOV function can be far larger for detection of moving targets than for detection of static targets. They showed that subjects can respond in less than 1 second to targets 20 degrees from the line of sight, if the targets are moving. If static targets are used, performance falls off rapidly beyond about 4 degrees from fixation (see Figure 5.27). This implies a UFOV of at least 40 degrees for the moving-targets task.

Motion as a User Interrupt

As we conduct more of our work in front of computer screens, there is an increasing need for signals that can attract a user's attention. Often someone is busy with a primary task, perhaps filling out forms or composing e-mail, while at the same time events may occur on other parts of the display that require attention. These *user interrupts* can alert us to an incoming message from a valued customer or a signal from a computer agent that has been out searching the Internet for information on the latest flu virus.

There are four basic visual requirements for a user interrupt:

1. A signal should be easily perceived, even if it is outside of the area of immediate focal attention.
2. If the user wishes to ignore the signal and attend to another task, the signal should continue to act as a reminder.
3. The signal should not be so irritating that it makes the computer unpleasant to use.
4. It should be possible to endow the signal with various levels of urgency.

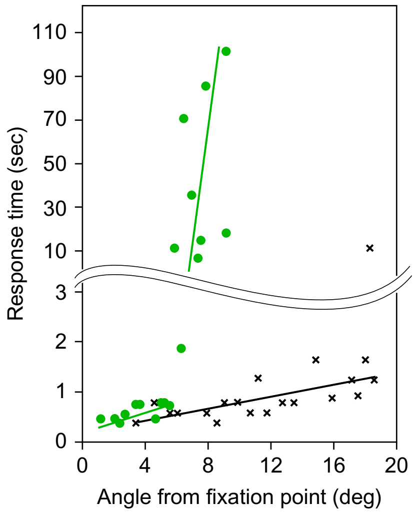


Figure 5.27 Results of a study by Peterson and Dugas (1972). The task was to detect small symbols representing aircraft in a simulation display. The circles show the response times from the appearances of static targets. The crosses show response times from the appearances of moving targets. Note the two different scales.

Essentially, the problem is how to attract the user's attention to information outside the central parafoveal region of vision (approximately the central 6 degrees). For a number of reasons, the options are limited. We have a low ability to detect small targets in the periphery of the visual field. Peripheral vision is color blind, which rules out color signals (Wyszecki & Stiles, 1982). Saccadic suppression (blindness during eye movements) means that some transitory event occurring in the periphery will generally be missed if it occurs during a saccadic movement (Burr & Ross, 1982). Taken together, these facts suggest that a single, abrupt change in the appearance of an icon is unlikely to be an effective signal.

The set of requirements suggests two possible solutions. One is to use auditory cues. In certain cases, these are a good solution, but they are outside the scope of this book. Another solution is to use blinking or moving icons. In a study involving shipboard alarm systems, Goldstein and Lamb (1967) showed that subjects were capable of distinguishing five flash patterns with approximately 98% reliability and that they responded with an average delay of approximately 2.0 seconds. Anecdotal evidence, however, indicates that a possible disadvantage of flashing lights or blinking cursors is that users find them irritating. Unfortunately, many web page designers generate a kind of animated chart junk; small, blinking animations with no functional purpose are often used to jazz up a page. Moving icons may be a better solution. Moving targets are detected more easily in the periphery than static targets (Peterson and Dugas, 1972). In a series of dual-task experiments, Bartram et al. (2003) had subjects carry out a primary task, either text editing or playing Tetris® or solitaire, while simultaneously monitoring for a change in an icon at the side of the display in the periphery of the visual field. The results showed that having an icon move was far more effective in attracting a user's attention than having it change color or shape. The advantage increased as the signal was farther from the focus of attention in the primary task. Another advantage of moving or blinking signals is that they can persistently attract attention, unlike a change in an icon, such as the raising of a mailbox flag, which fades rapidly from attention. Also, although rapid motions are annoying, slower motions need not be and they can still support a low level of awareness (Ware et al., 1992).

Interestingly, more recent work has suggested that it may not be motion *per se* that attracts attention, but the appearance of a new object in the visual field (Hillstrom and Yantis, 1994; Enns et al., 2001). This seems right; after all, we are not constantly distracted in an environment of swaying trees or people moving about on a dance floor. It also makes ecological sense; when early man was outside a cave, intently chipping a lump of flint into a hand axe, or when early woman was gathering roots out on the grasslands, awareness of emerging objects in the periphery of vision would have had clear survival value. Such a movement might have signaled an imminent attack. Of course, the evolutionary advantage goes back much further than this. Monitoring the periphery of vision for moving predators or prey would provide a survival advantage for most animals. Thus, the most effective reminder might be an object that moves into view, disappears, and then reappears every so often. In a study that measured the eye movements made while viewing multimedia presentations, Faraday and Sutcliffe (1997) found that the onset of motion of an object generally produced a shift of attention to that object.

Conclusion

This chapter has provided an introduction to the early stages of vision, in which billions of neurons act in parallel to extract elementary aspects of form, color, texture, motion, and stereoscopic depth. The fact that this processing is done for each point of the visual field means that objects differentiated in terms of these simple low-level features pop out and can be easily found. These low-level filters are not unbiased; they are tuned by the effects of top-down attention. This means that to a great extent what we need to see as well as what we expect to see will have a large influence on what we actually see.

For glyphs to be seen rapidly, they must stand out clearly from all other objects in their near vicinity on at least one coding dimension. In a display of large symbols, a small symbol will stand out. In a display of blue, green, and gray symbols, a red symbol will stand out. Because only simple basic visual properties guide visual search, glyphs and symbols that are distinctive in terms of more complex combinations of features cannot be easily found.

The lessons from this chapter have to do with fundamental tradeoffs in design choices about whether to use color, shape, texture, or motion to display a particular set of variables. These basic properties provide a set of channels that can be used to code information.

There is more visual interference within channels. The basic rule is that, in terms of low-level properties, "like" interferes with "like." If we have a set of small symbols on a textured background, a texture with a grain size similar to that of the symbols will make them difficult to see.

There is more separability between channels. If we wish to be able to read data values from different data dimensions, each of these values should be mapped to a different display channel. Mapping one variable to color and another to glyph orientation will make them independently readable. If we map one variable to height and another to width, they will be read more holistically. If we have a set of symbols that are difficult to see because they are on a textured background, they can be made to stand out by using another coding channel; having the symbols oscillate will also make them distinct. The way to differentiate variables readily is to employ more perceptual channels. Unfortunately, although this solves one problem, it creates another. We have to decide which variable to map to color, to shape, and to texture, and we have to worry about which mappings will be most intuitive for the intended audience. These are difficult design decisions.

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CHAPTER SIX

Static and Moving Patterns

Data analysis is about finding patterns that were previously unknown or that depart from the norm. The stock market analyst looks for any pattern of variables that may predict a future change in price or earnings. The marketing analyst is interested in perceiving trends and patterns in a customer database. The scientist searches for patterns that may confirm or refute an hypothesis. When we look for patterns, we are making visual queries that are key to visual thinking. Sometimes the queries are vague; we are on the lookout for a variety of structures in the data or any exception to a general rule. Sometimes they are precise, as when we look for a positive trend in a graph.

The visual brain is a powerful pattern-finding engine; indeed, this is the fundamental reason why visualization techniques are becoming important. There is no other way of presenting information so that structures, groups, and trends can be discovered among hundreds of data values. If we can transform data into the appropriate visual representation, its structure may be revealed, but what is the best mapping from data to display? What does it take for us to see a group? How can two-dimensional (2D) space be divided into perceptually distinct regions? Under what conditions are two patterns recognized as similar? What constitutes a visual connection between objects? These are some of the perceptual questions addressed in this chapter. The answers are central to visualization, because most data displays are two dimensional and pattern perception deals with the extraction of structure from 2D space. Consider again our three-stage model of perception (illustrated in Figure 6.1). At the early stages of feature abstraction, the visual image is analyzed in terms of primitive elements of form, motion, color, and stereoscopic depth. At the middle 2D pattern-perception stage, active processes driven by top-down visual queries cause contours

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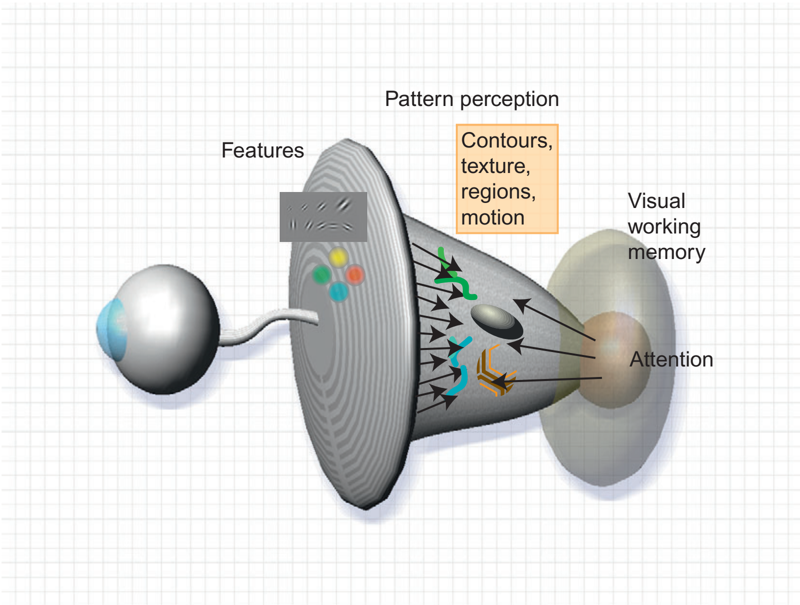


Figure 6.1 Pattern perception occurs in a middle ground where bottom-up feature processing meets the requirements of top-down active attention.

to be formed, distinct regions to be segmented, and connections to be made. At the top level, objects and scenes are discovered, using information about the connections between component parts, shape-from-shading information, and so on. Pattern perception can be thought of as a set of mostly 2D processes occurring between feature analysis and full object perception, although aspects of three-dimensional space perception, such as stereoscopic depth and structure-from-motion, can be considered particular kinds of pattern perception. Finally, objects and significant patterns are pulled out by attentional processes to meet the needs of the task at hand. There are radical differences in the kinds of processing that occur at the different stages. In the early stages, massively parallel processing of the entire image occurs. This drives perception from the bottom up, but object and pattern recognition is driven from the top down through active attention, meeting the requirements of visual thinking. At the highest level, only one to five objects (or simple patterns) are held in visual working memory from one fixation to the next, as we make comparisons and conduct visual searches.

Pattern perception is the flexible middle ground where objects are extracted from patterns of features. Active processes of attention reach down into the pattern space to keep track of those objects and to analyze them for particular tasks; the essentially bottom-up processing of feature primitives meets the top-down processes of cognitive perception. Rensink (2000) called the middle ground a *proto-object flux*. According to Ullman (1984), active processes under top-down control, called *visual routines*, pull out only a small number of patterns at any given instant.

Our knowledge of pattern perception can be distilled into abstract design principles stating how to organize data so that important structures will be perceived. If we can map information structures to readily perceived patterns, then those structures will be more easily interpreted.

Gestalt Laws

The first serious attempt to understand pattern perception was undertaken by a group of German psychologists who, in 1912, founded what is known as the Gestalt school of psychology. The group consisted principally of Max Westheimer, Kurt Koffka, and Wolfgang Kohler (see Koffka, 1935, for an original text). The word *Gestalt* simply means "pattern" in German. The work of the Gestalt psychologists is still valued today because they provided a clear description of many basic perceptual phenomena. They produced a set of Gestalt laws of pattern perception. These are robust rules that describe the way we see patterns in visual displays, and, although the neural mechanisms proposed by these researchers to explain the laws have not withstood the test of time, the laws themselves have proved to be of enduring value. The Gestalt laws easily translate into a set of design principles for information displays. Eight Gestalt laws are discussed here: proximity, similarity, connectedness, continuity, symmetry, closure, relative size, and common fate (the last concerns motion perception and appears later in the chapter).

Proximity

Spatial proximity is a powerful perceptual organizing principle and one of the most useful in design. Things that are close together are perceptually grouped together. Figure 6.2 shows two arrays of dots that illustrate the proximity principle. Only a small change in spacing causes us to change what is perceived from a set of rows, in Figure 6.2(a), to a set of columns, in Figure 6.2(b). In Figure 6.2(c), the existence of two groups is perceptually inescapable. Proximity is not the only factor in predicting perceived groups. In Figure 6.3, the dot labeled x is perceived to be part of cluster a rather than cluster b, even though it is as close to the other points in cluster b as they are to each other. Slocum (1983) called this the *spatial concentration* principle; we perceptually group regions of similar element density. The application of the proximity law in display design is straightforward.

[G6.1] Place symbols and glyphs representing related information close together.

In addition to the perceptual organization benefit, there is also a perceptual efficiency to using proximity. Because we more readily pick up information close to the fovea, less time and effort will be spent in neural processing and eye movements if related information is spatially grouped.

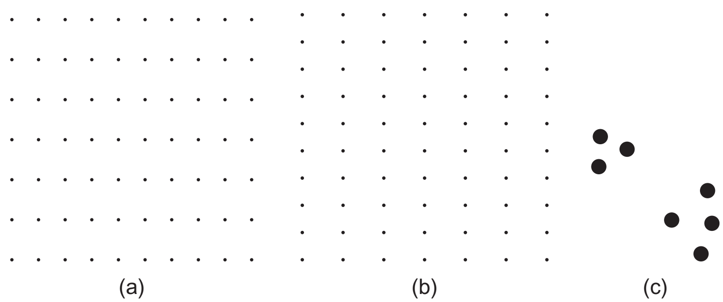


Figure 6.2 Spatial proximity is a powerful cue for perceptual organization. A matrix of dots is perceived as rows on the left (a) and columns on the right (b). In (c) we perceive two groups of dots because of proximity relationships.

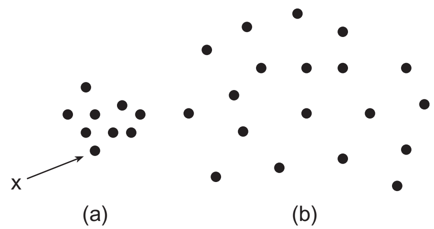


Figure 6.3 The principle of spatial concentration. The dot labeled x is perceived as part of cluster a rather than cluster b.

Similarity

The shapes of individual pattern elements can also determine how they are grouped. Similar elements tend to be grouped together. In Figure 6.4(a, b) the similarity of the elements causes us to see rows more clearly. In terms of perception theory, the concept of similarity has been largely superseded. The channel theory and the concepts of integral and separable dimensions provide much more detailed analysis and better support for design decisions. Two different ways of visually separating row and column information are shown in Figure 6.4(c) and (d). In Figure 6.4(c), integral color and grayscale coding is used. In Figure 6.4(d), green is used to delineate rows and texture is used to delineate columns. Color and texture are separate channels, and the result is a pattern that can be more readily visually segmented either by rows or by columns. This technique can be useful if we are designing so that users can easily attend to either one pattern or the other.

[G6.2] When designing a grid layout of a data set, consider coding rows and/or columns using low-level visual channel properties, such as color and texture.

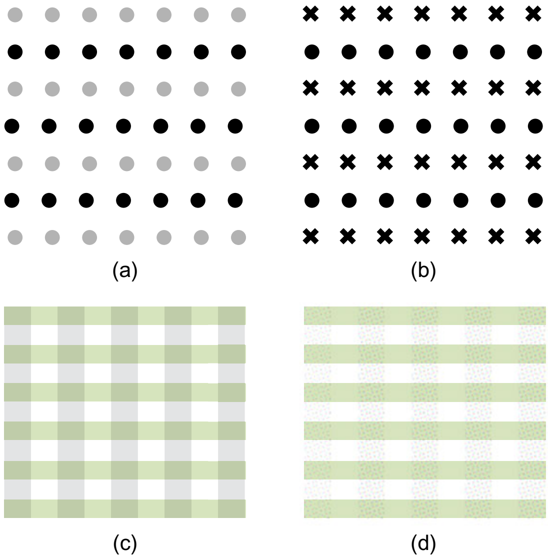


Figure 6.4 (a, b) According to the Gestalt psychologists, similarity between the elements in alternate rows causes the row percept to dominate. (c) Integral dimensions are used to delineate rows and columns. (d) When separable dimensions (color and texture) are used, it is easier to attend separately to either the rows or the columns.

Connectedness

Palmer and Rock (1994) argued that connectedness is a fundamental Gestalt organizing principle that the Gestalt psychologists overlooked. The demonstrations in Figure 6.5 show that connectedness can be a more powerful grouping principle than proximity, color, size, or shape. Connecting different graphical objects by lines is a very powerful way of expressing that there is some relationship between them. Indeed, this is fundamental to the node–link diagram, one of the most common methods of representing relationships between concepts.

> **[G6.3]** To show relationships between entities, consider linking graphical representations of data objects using lines or ribbons of color.

Continuity

The Gestalt principle of continuity states that we are more likely to construct visual entities out of visual elements that are smooth and continuous, rather than ones that contain abrupt changes in direction. (See Figure 6.6.) The principle of good continuity can be applied to the problem of drawing diagrams consisting of networks of nodes and the links between them. It should be easier to identify the sources and destinations of connecting lines if they are smooth and continuous. This point is illustrated in Figure 6.7.

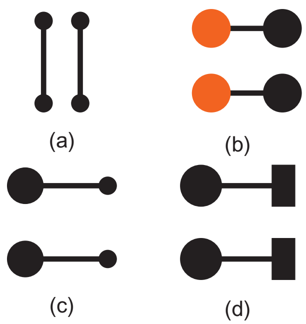


Figure 6.5 Connectedness is a powerful grouping principle that is stronger than (a) proximity, (b) color, (c) size, or (d) shape.

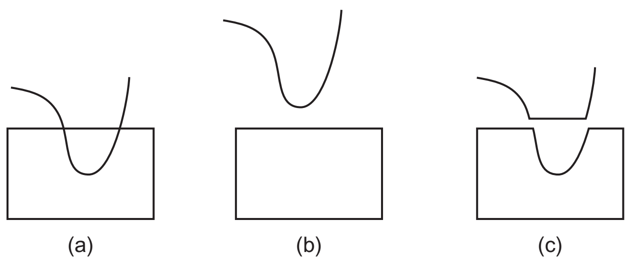


Figure 6.6 The pattern on the left (a) is perceived as a smoothly curved line overlapping a rectangle (b) rather than as the more angular components shown in (c).

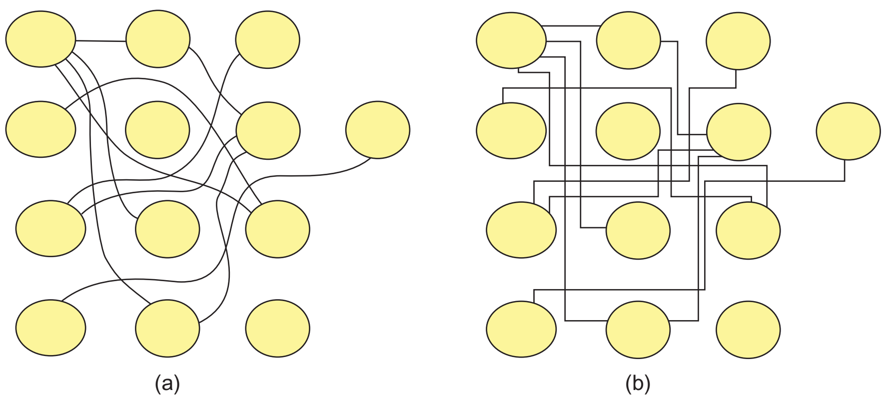


Figure 6.7 In (a), smooth continuous contours are used to connect nodes in the diagram; in (b), lines with abrupt changes in direction are used. It is much easier to perceive connections with the smooth contours.

Symmetry

Symmetry can provide a powerful organizing principle. The symmetrically arranged pairs of lines in Figure 6.8 are perceived more strongly as forming a visual whole than the pair of parallel lines. A possible application of symmetry is in tasks in which data analysts are looking for similarities between two different sets of time-series data. It may be easier to perceive similarities if these time series are arranged using vertical symmetry, as shown in Figure 6.9, rather than using the more conventional parallel plots.

To take advantage of symmetry the important patterns must be small. Research by Dakin and Herbert (1998) suggests that we are most sensitive to symmetrical patterns that are small, less than 1 degree in width and 2 degrees in height, and centered around the fovea. The display on the right in Figure 6.9 is far too large to be optimal from this point of view.

We more readily perceive symmetries about vertical and horizontal axes, as shown in Figure 6.10(a, b); however, this bias can be altered with a frame of reference provided by a larger-scale pattern, as shown in Figure 6.10(c) and (d). See Beck et al. (2005).

[G6.4] Consider using symmetry to make pattern comparisons easier, but be sure that the patterns to be compared are small in terms of visual angle (<1 degree horizontally and <2 degrees vertically). Symmetrical relations should be arranged on horizontal or vertical axes unless some framing pattern is used.

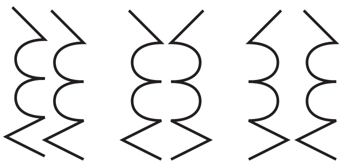


Figure 6.8 The pattern on the left consists of two identical parallel contours. In each of the other two patterns, one of the contours has been reflected about a vertical axis, producing bilateral symmetry. The result is a much stronger sense of a holistic figure.

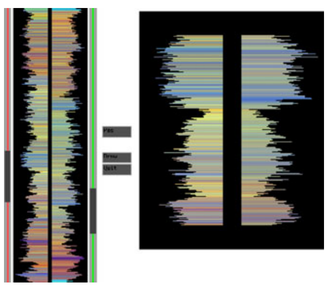


Figure 6.9 An application designed to allow users to recognize similar patterns in different time-series plots. The data represents a sequence of measurements made on deep ocean drilling cores. Two subsets of the extended sequences are shown on the right.

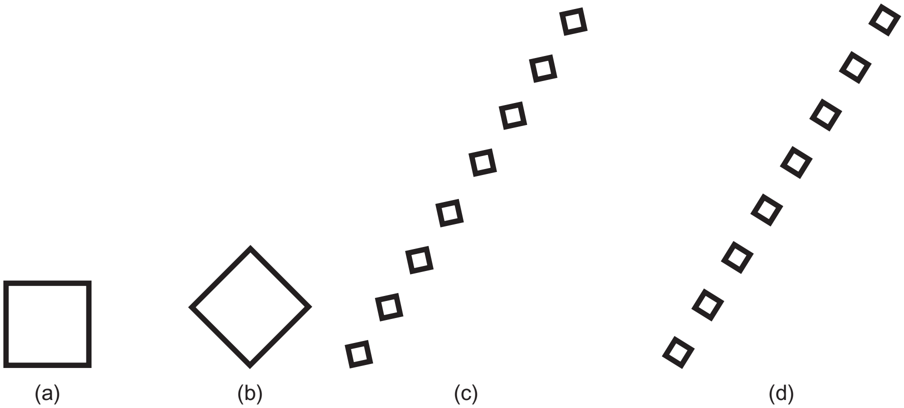


Figure 6.10 Because symmetries about vertical and horizontal axes are more readily perceived, (a) is seen as a square and (b) is seen as diamond. (c, d) A larger pattern can provide a frame of reference that defines the axes of symmetry; (c) is seen as a line of diamonds and (d) as a line of squares.

Closure and Common Region

A closed contour tends to be seen as an object. The Gestalt psychologists argued that there is a perceptual tendency to close contours that have gaps in them. This can help explain why we see Figure 6.11(a) as a complete circle and a rectangle rather than as a circle with a gap in it as in Figure 6.11(b).

Wherever a closed contour is seen, there is a very strong perceptual tendency to divide regions of space into "inside" or "outside" the contour. A region enclosed by a contour becomes a *common region* in the terminology of Palmer (1992), who showed common region to be a much stronger organizing principle than simple proximity.

Closed contours are widely used to visualize set concepts in Venn–Euler diagrams. In an Euler diagram, we interpret the region inside a closed contour as defining a set of elements. Multiple closed contours are used to delineate the overlapping relationships among different sets. A Venn diagram is a more restricted form of Euler diagram containing all possible regions of overlap. The two most important perceptual factors in this kind of diagram are closure and continuity. A fairly complex structure of overlapping sets is illustrated in Figure 6.12, using an Euler diagram. This kind of diagram is almost always used in teaching introductory set theory, and this in itself is evidence for its effectiveness. Students easily understand the diagrams, and they can transfer this understanding to the more difficult formal notation (Stenning & Oberlander, 1994).

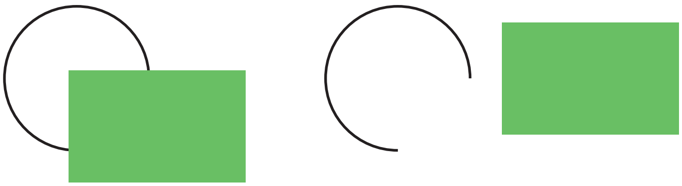


Figure 6.11 The Gestalt principle of closure holds that neural mechanisms operate to find perceptual solutions involving closed contours. In (a), we see a circle behind a rectangle, not a broken ring as in (b).

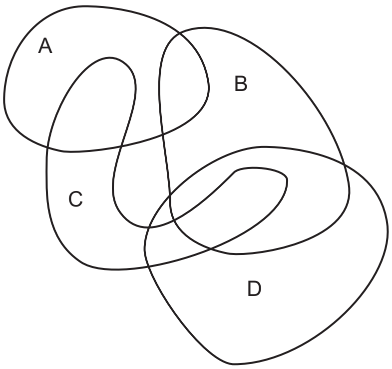


Figure 6.12 An Euler diagram. This diagram tells us (among other things) that entities can simultaneously be members of sets A and C but not of A, B, and C. Also, anything that is a member of both B and C is also a member of D. These rather difficult concepts are clearly expressed and understood by means of closed contours.

When the boundary of a contour-defined region becomes complex, what is inside or outside may become unclear. In such cases, using color, texture, or Cornsweet contours (discussed in Chapter 3) will be more effective (Figure 6.13). Although simple contours are generally used in Euler diagrams to show set membership, we can effectively define more complex sets of overlapping regions by using color and texture in addition to simple contours (Figure 6.14). Figure 6.15 shows an example from Collins et al. (2009) where both transparent color and contour are used to define extremely convoluted boundaries for three overlapping sets.

[G6.5] Consider putting related information inside a closed contour. A line is adequate for regions having a simple shape. Color or texture can be used to define regions that have more complex shapes.

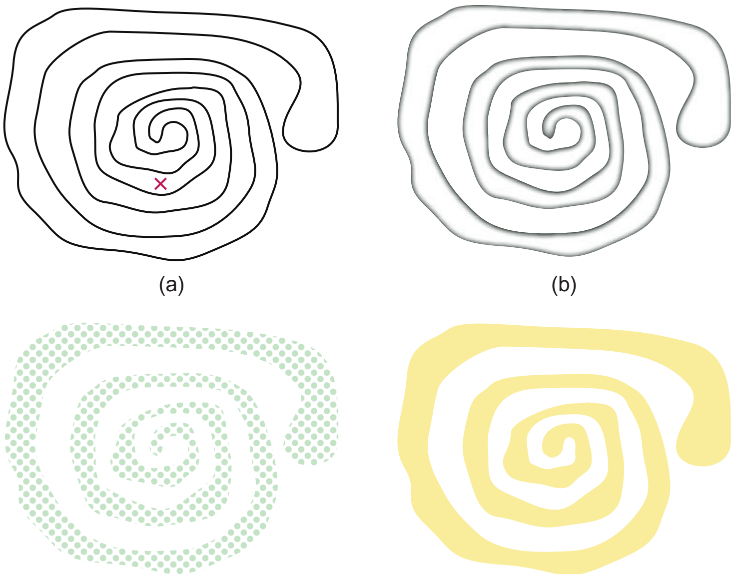


Figure 6.13 When the shape of the region is complex, a simple contour (shown in the upper left) is inadequate. (a) It is not easy to see if the x is inside or outside of the enclosed region. Common region can be defined less ambiguously by means of (b) a Cornsweet (1970) edge, (c) texture, or (d) color.

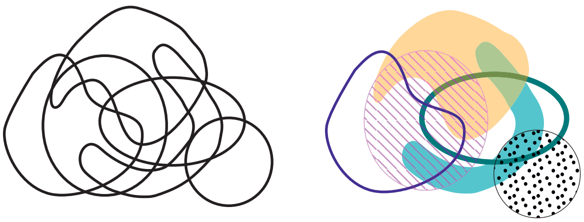


Figure 6.14 An Euler diagram enhanced using texture and color can convey a more complex set of relations than a conventional Euler diagram using only closed contours.

> **[G6.6]** To define multiple overlapping regions, consider using a combination of line contour, color, texture, and Cornsweet contours.

Both closure and closed contours are critical in segmenting the monitor screen in windows-based interfaces. The rectangular overlapping boxes provide a strong segmentation cue, dividing the display into different regions. In addition, rectangular frames provide frames of reference: The position of every object within the frame tends to be judged relative to the enclosing frame (see Figure 6.16).

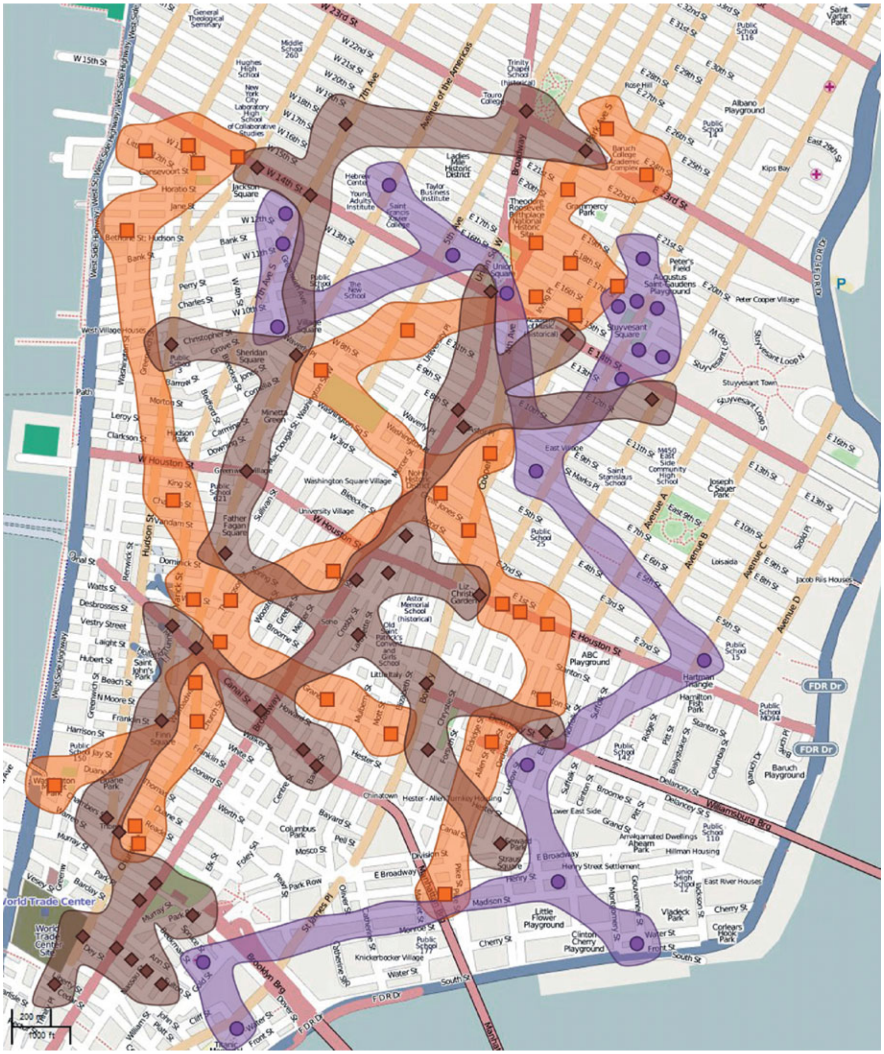


Figure 6.15 Both contour- and color-defined regions have been added to make clear the distribution of hotels (orange), subway stations (brown), and medical clinics (purple). (*From Collins et al. (2009). Reproduced with permission.*)

Figure and Ground

Gestalt psychologists were also interested in what they called *figure–ground* effects. A *figure* is something objectlike that is perceived as being in the foreground. The *ground* is whatever lies behind the figure. In general, smaller components of a pattern tend to be perceived as objects. In Figure 6.17(a), a black propeller is seen on a white background, as opposed to the white areas being perceived as objects.

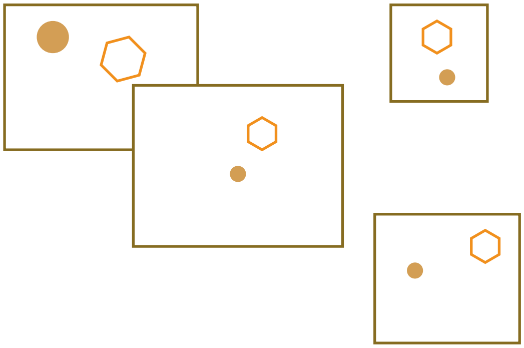


Figure 6.16 Closed rectangular contours strongly segment the visual field. They also provide reference frames. The positions and sizes of the enclosed shapes are, to some extent, interpreted with respect to the surrounding frame.

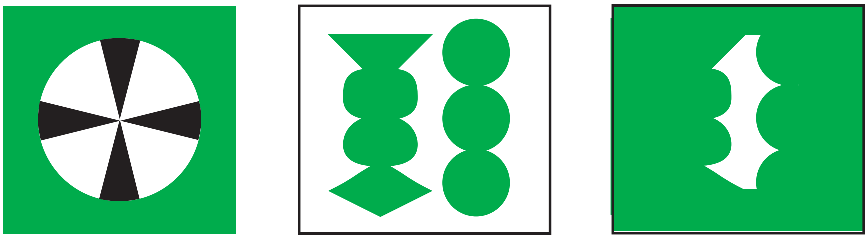


Figure 6.17 (a) The black areas are smaller and therefore more likely to be perceived as an object. It is also easier to perceive patterns that are oriented horizontally and vertically as objects. (b) The green areas are seen as figures because of several Gestalt factors, including size and closed form. The area between the green shapes in (c) is generally not seen as a figure.

The perception of figure as opposed to ground can be thought of as part of the fundamental perceptual act of identifying objects. All of the Gestalt laws contribute to creating a figure, along with other factors that the Gestalt psychologists did not consider, such as texture segmentation. Closed contour, symmetry, and the surrounding white area all contribute to the perception of the two shapes in Figure 6.17(b) as figures, as opposed to cut-out holes. But, by changing the surroundings, as shown in Figure 6.17(c), the irregular shape that was perceived as a gap in Figure 6.17(b) can be made to become the figure.

> **[G6.7]** Use a combination of closure, common region, and layout to ensure that data entities are represented by graphical patterns that will be perceived as figures, not ground.

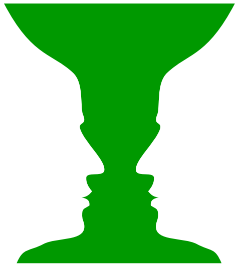


Figure 6.18 Rubin's Vase. The cues for figure and ground are roughly equally balanced, resulting in a bistable percept of either two faces or a vase.

Figure 6.18 shows the classic Rubin's Vase figure, in which it is possible to perceive either two faces, nose to nose, or a green vase centered in the display. The fact that the two percepts tend to alternate illustrates how competing active processes are involved in constructing figures from the pattern; however, the two percepts are driven by very different mechanisms. The vase percept is supported mostly by symmetry and being a closed region. Conversely, the faces percept is mostly driven by prior knowledge, not gestalt factors. It is only because of the great importance of faces that they are so readily seen. The result is a competition between high-level and mid-level processes.

More on Contours

We now return to the topic of contours to discuss what recent research tells us about how they are processed in the brain. Contours are continuous, elongated boundaries between regions of a visual image, and the brain is exquisitely sensitive to their presence. A contour can be defined by a line, by a boundary between regions of different color, by stereoscopic depth, by motion patterns, or by the edge of a region of a particular texture. Contours can even be perceived where there are none. Figure 6.19 illustrates an illusory contour; a ghostly boundary of a blobby shape is seen even where none is physically present (see Kanizsa, 1976). Because the process that leads to the identification of contours is seen as fundamental to object perception, contour detection has received considerable attention from vision researchers, and contours of various types are critical to many aspects of visualization.

A set of experiments by Field et al. (1993) proved to be a landmark in placing the Gestalt notion of continuity on a firmer scientific basis. In these experiments, subjects had to detect the presence of a continuous path in a field of 256 randomly oriented Gabor patches (see Chapter 5 for a discussion of Gabor functions). The setup is illustrated schematically in Figure 6.20. The results showed that subjects were very good at perceiving a smooth path through a sequence of patches. As one might expect, continuity between Gabor patches oriented in straight lines was the easiest to perceive. More interesting, even quite wiggly paths were readily seen if the Gabor elements were aligned as shown in

Figure 6.19 Most people see a faint illusory contour surrounding a blobby shape at the center of this figure.

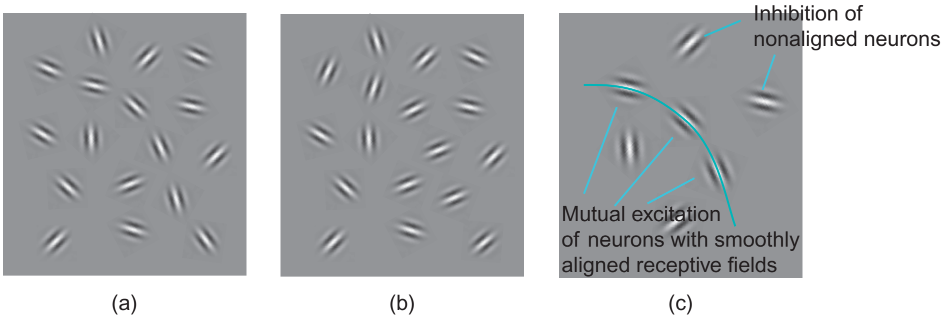


Figure 6.20 An illustration of the experiments conducted by Field et al. (1993). If the elements are aligned as shown in (a) so that a smooth curve can be drawn through some of them, a curve is seen. If the elements are at right angles, no curve is seen (b). This effect is explained by mutual excitation of neurons (c).

Figure 6.20(a). The theory underlying contour perception is that there is mutual reinforcement between neurons that have receptive fields that are smoothly aligned; there is inhibition between neurons with nonaligned receptive fields. The result is a kind of winner-take-all effect. Stronger contours beat out weaker contours.

Higher order neurophysiological mechanisms of contour perception are not well understood. One result, however, is intriguing. Gray et al. (1989) found that cells with collinear receptive fields tend to fire in synchrony. Thus, we do not need to propose higher order feature detectors, responding to more and more complex curves, to understand the neural encoding of contour information. Instead, it may be that groups of cells firing in synchrony is the way that the brain holds related pattern elements in mind. Theorists have suggested a fast enabling link, a kind of rapid feedback system, to achieve the firing of cells in synchrony (Singer & Gray, 1995). The theory of synchronous firing binding contours is still controversial; however, there is agreement that *some* neural mechanism enhances the response of neurons that lie along a smoothly connected edge (Li, 1998; Grossberg & Williamson, 2001).

Representing Vector Fields: Perceiving Orientation and Direction

The basic problem of representing a vector can be broken down into three components: the representation of vector magnitude, the representation of orientation, and the representation of direction with respect to a particular orientation. Figure 6.21 illustrates this point. Some techniques display one or two components, but not all three; for example, wind speed (magnitude) can be shown as a scalar field by means of color coding.

There are direct applications of the Field et al. (1993) theory of contour perception in displaying vector field data. A common technique is to create a regular grid of oriented elements, such as the one shown in Figure 6.22(a). The theory suggests that head-to-tail alignment should make it easier to see the flow patterns (Ware, 2008). When the line segments are displaced so that smooth contours can be drawn between them, the flow pattern is much easier to see, as shown in Figure 6.22(c).

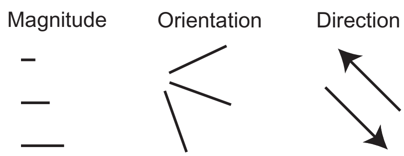


Figure 6.21 The components of a vector.

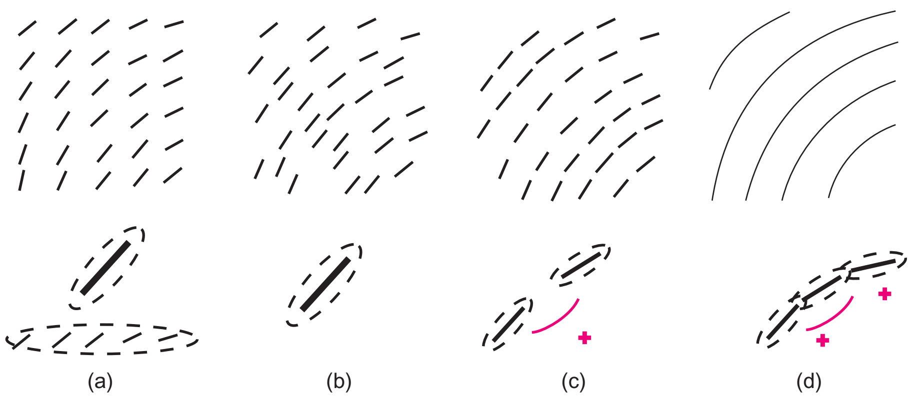


Figure 6.22 The results of Field et al. (1993) suggest that vector fields should be easier to perceive if smooth contours can be drawn through elements representing the flow. (a) A gridded pattern will weakly stimulate neurons with oriented receptive fields but also cause the perception of false contours from the rows and columns. (b) Line segments in a jittered grid will not create false contours. (c) If contour segments are aligned, mutual reinforcement will occur. (d) The strongest response will occur with continuous contours.

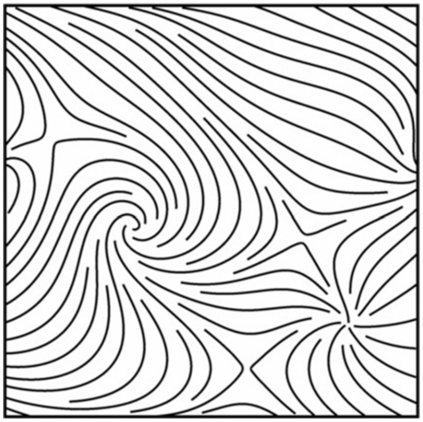


Figure 6.23 Streamlines can be an effective way to represent vector field or flow data. But here the direction is ambiguous and the magnitude is not shown. (*From Turk & Banks, 1996; with permission.*)

Instead of the commonly used grid of small arrows, one obvious and effective way of representing vector fields is through the use of continuous contours; a number of effective algorithms exist for this purpose. Figure 6.23 shows an example from Turk and Banks (1996). This effectively illustrates the orientation of the vector field, although it is ambiguous in the sense that for a given contour there can be two directions of flow. In addition, Figure 6.23 does not show magnitude.

Comparing 2D Flow Visualization Techniques

Laidlaw et al. (2001) carried out an experimental comparison of the six different flow visualization methods, illustrated in Figure 6.24: (a) arrows on a regular grid; (b) arrows on a jittered grid to reduce perceptual aliasing effects; (c) triangle icons, with icon size proportional to field strength and density inversely related to icon size (Kirby et al., 1999); (d) line integral convolution (Cabral & Leedom, 1993); (e) large-head arrows along a streamline using a regular grid (Turk & Banks, 1996); and (f) large-head arrows along streamlines using a constant spacing algorithm (Turk & Banks, 1996).

In order to evaluate any visualization, it is necessary to specify a set of tasks. Laidlaw et al. (2001) had subjects identify critical points as one task. These are points in a vector or flow field where the vectors have zero magnitude. The results showed the arrow-based methods illustrated in Figure 6.24(a) and (b) to be the least effective for identifying the locations of these points. A second task involved perceiving advection trajectories. An *advection trajectory* is the path taken by a particle dropped in a flow. The streamline methods of Turk and Banks, shown in Figure 6.24(f), proved best for showing advection. The line integral convolution method, shown in Figure 6.24(d),

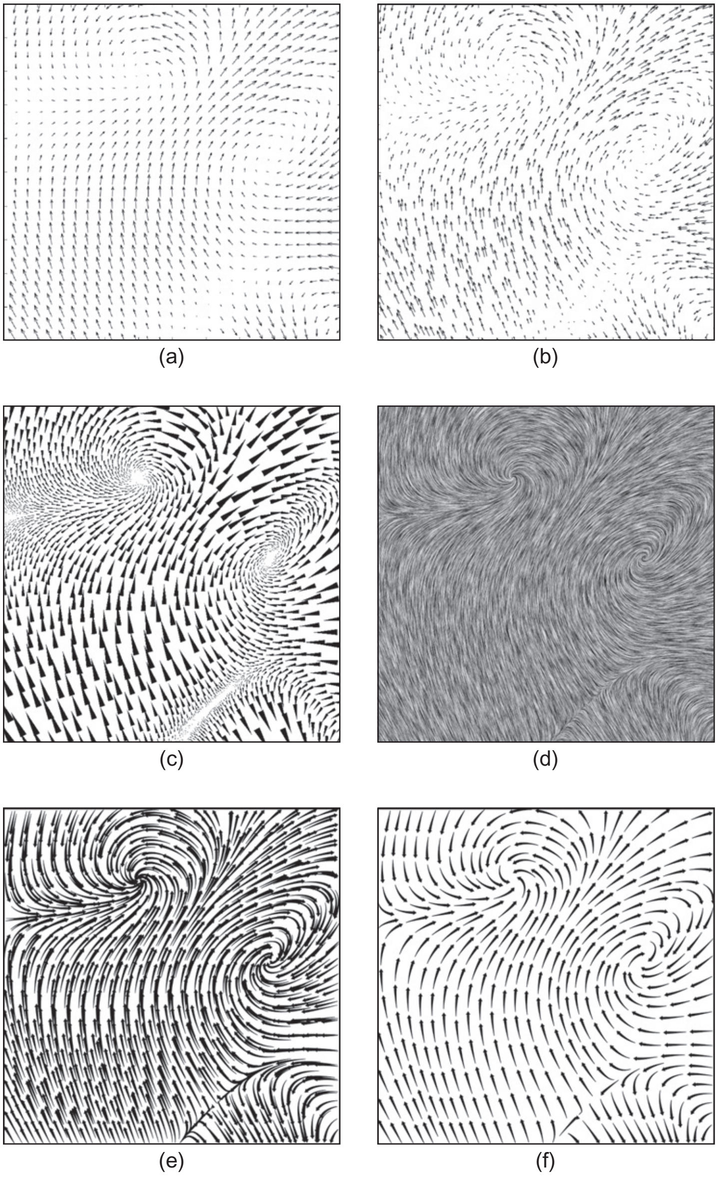


Figure 6.24 Six different flow visualization techniques evaluated by Laidlaw et al. (2001). (*From Laidlaw et al. (2001). Reproduced with permission*.)

was by far the worst for advection, probably because it does not unambiguously identify direction. It is also worth pointing out that three of the methods do not show vector magnitude at all; see Figure 6.24(d, e, f).

Although the study done by Laidlaw et al. (2001) was the first serious comparative evaluation of the effectiveness of vector field visualization methods, it is by no means exhaustive. There are alternative visualizations, and those shown have many possible variations: longer and shorter line segments, color variations, and so on. In addition, the tasks studied by Laidlaw et al. did not include all of the important visualization tasks that are likely to be carried out with flow visualizations.

Here is a more complete list:

- Judging the speed, orientation, and direction at an arbitrary point
- Identifying the location and nature of critical points
- Judging an advection trajectory
- Perceiving patterns of high and low speed (or magnitude)
- Perceiving patterns of high and low vorticity (sometimes called *curl*)
- Perceiving patterns of high and low turbulence

Both the kinds and the scale of patterns that are important will vary from one application to another; small-scale detailed patterns, such as eddies, will be important to one researcher, whereas large-scale patterns will interest another.

The problem of optimizing flow display may not be quite so complex and multifaceted as it would first seem. If we ignore the diverse algorithms and think of the problem in purely visual terms, then the various display methods illustrated in Figure 6.24 have many characteristics in common. They all consist principally of contours oriented in the flow direction, although these contours have different characteristics in terms of length, width, and shape. The shaft of an arrow is a short contour. The line integral convolution method illustrated in Figure 6.24(d) produces a very different-looking, blurry result; however, something similar could be computed using blurred contours. Contours that vary in shape and gray value along their lengths could be expressed with two or three parameters. The different degrees of randomness in the placement of contours could be parameterized; thus, we might consider the various 2D flow visualization methods as part of a family of related methods—different kinds of flow-oriented contours. Considered in this way, the display problem becomes one of optimizing the various parameters that control how vector magnitude, orientation, and direction are mapped to contour in the display.

Showing Direction

In order to show direction, something must be added to a contour to give it asymmetry along its path. A neural mechanism that can account for the perception of asymmetric endings of contours is called the *end-stopped cell.* Many V1 neurons respond strongly to a contour that ends in the receptive field of the cell, but only coming from one direction (Heider et al., 2000). The more asymmetry there is in the way contour segments terminate, the greater the asymmetry in neural response, so this can provide a mechanism for detection of flow direction (Ware, 2008). Figure 6.25 illustrates this concept.

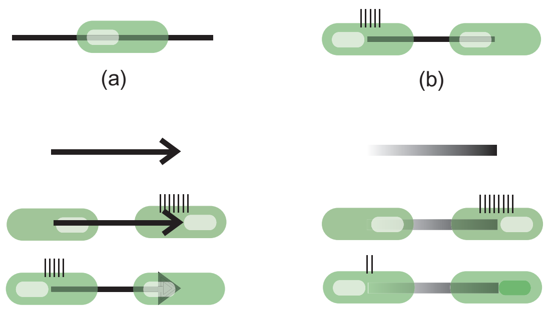


Figure 6.25 (a) An end-stopped cell (shown as a green blob) will not respond when a line passes through it. (b) It responds only when the line terminates in the cell from a particular direction. (c) This asymmetry of response will weakly differentiate the heads of arrows from their tails. (d) It will more strongly differentiate the ends of a broad line with a gradient along its length. The little bars represent neuron firing rates.

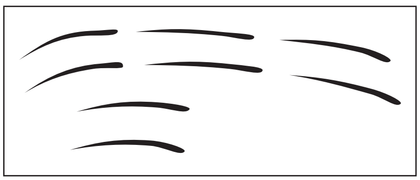


Figure 6.26 Drawing in a style based on the pen strokes used by Edmund Halley (1696), discussed in Tufte (1983), to represent the trade winds of the North Atlantic. Halley described the wind direction as being given by "the sharp end of each little stroak pointing out that part of the horizon, from whence the wind continually comes."

Conventional arrowheads are one way of providing directional asymmetry, as in Figure 6.25(c), but the asymmetric signal is relatively weak. Arrowheads also produce visual clutter because the contours from which they are constructed are not tangential to the vector direction.

An interesting way to resolve the flow direction ambiguity is provided in a 17th-century vector field map of North Atlantic wind patterns by Edmund Halley (discussed in Tufte, 1983). Halley's elegant pen strokes, illustrated in Figure 6.26, are shaped like long, narrow airfoils oriented to the flow, with the wind direction given by the blunt end. Halley also arranges his strokes along streamlines. These can produce a stronger asymmetric signal than an arrowhead. We verified experimentally that strokes like Halley's are unambiguously interpreted with regard to direction (Fowler & Ware, 1989).

Fowler and Ware (1989) developed a new method for creating an unambiguous sense of vector field direction that involves varying the gray level along the length of a stroke. This is illustrated in Figure 6.27. If one end of the stroke is given the background gray

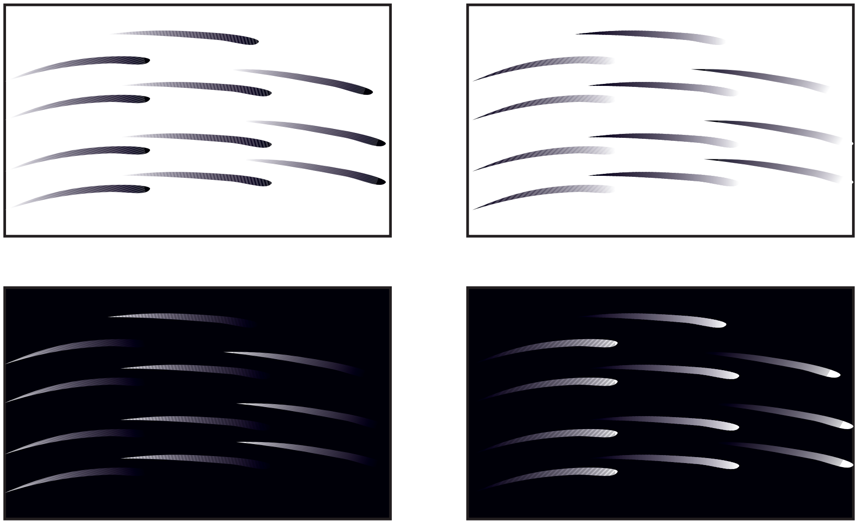


Figure 6.27 Vector direction can be unambiguously given by means of lightness change along the particle trace, relative to the background. This gives the greatest asymmetry between the different ends of each trace.

level, the stroke direction is perceived to be in the direction of change away from the background gray level. In our experiments, the impression of direction produced by lightness change completely dominated that given by shape. This is what the end-stopped cell theory predicts—the greater the asymmetry between the two ends of each contour, the more clearly the direction will be seen. Unfortunately, the perception of orientation may be somewhat weakened. The problem is to get both a strong directional response and a strong orientation response.

We can distill the above discussion into two guidelines.

> **[G6.8]** For vector field visualizations, use contours tangential to streamlines to reveal the orientation component.

> **[G6.9]** To represent flow direction in a vector field visualization, use streamlets with heads that are more distinct than tails, based on luminance contrast. A *streamlet* is a glyph that is elongated along a streamline and which induces a strong response in neurons sensitive to orientations tangential to the flow.

To reveal the magnitude component of a vector field, we can fall back on the basic principle of using something that produces a stronger neural signal to represent fast flow or a stronger field. Figure 6.28 gives an example that follows both guidelines G6.8 and G6.9, and in addition uses longer and wider graphical elements to show regions of stronger flow (Mitchell et al., 2009).

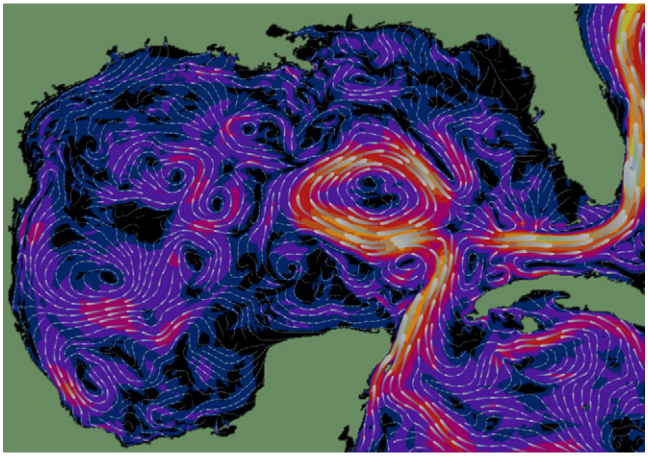


Figure 6.28 The surface currents in the Gulf of Mexico from the AMSEAS model. Head-to-tail elements are used, with each element having a more distinct head than tail. Speed is given by width, length, and background color.

[G6.10] For vector field visualizations, use more distinct graphical elements to show greater field strength or speed. They can be wider, longer, more contrasting, or faster moving.

Texture: Theory and Data Mapping

Texture can provide a whole set of subchannels for displaying information, and so far we have said little about how to accomplish this. Like color, we can use texture as a nominal code, displaying different categories of information, or as a method for representing quantity over a spatial map, using texture to provide ordinal or interval coding.

Texture segmentation is the name given to the process whereby the brain divides the visual world into regions based on texture. The Gabor model of V1 receptive fields, introduced in Chapter 5, is a key component of most theories of what makes a texture distinctive (Turner, 1986; Bovik et al., 1990; Malik & Perona, 1990). These theories of texture segmentation rely on the same set of feature maps that were introduced in Chapter 5 to account for rapid search of individual targets, so it will come as no surprise that the rules of texture segmentation are very similar to the rules for individual target salience. Indeed, the boundary between having many glyphs and having a texture is poorly defined, and texture can be thought of as a densely populated field of small glyphs.

The Malik and Perona (1990) type of segmentation model is illustrated in Figure 6.29. It has three main stages. In the first stage, feature maps of Gabor filters respond strongly to regions of texture where particular spatial frequencies and orientations predominate. In the next stage, the output from this early stage is low-pass filtered.

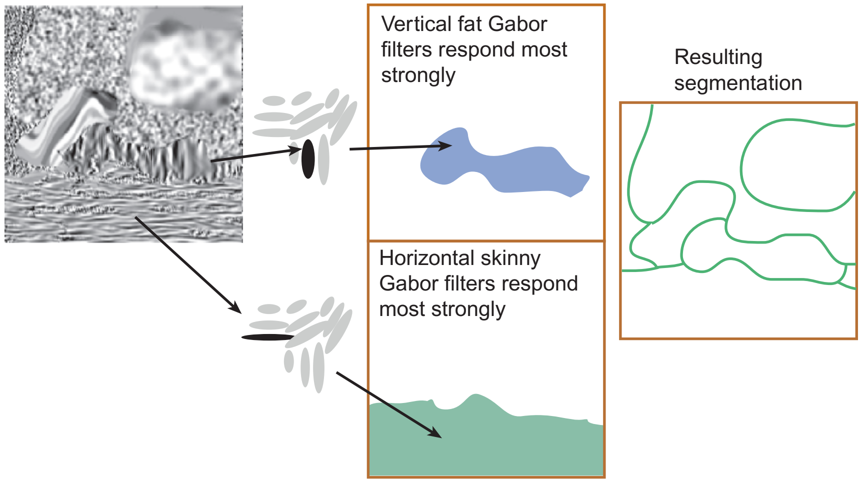


Figure 6.29 A texture segmentation model. Two-dimensional feature maps of Gabor detectors filter every part of the image for all possible orientations and sizes. Extended areas that excite similar classes of detectors form perceived regions of the image.

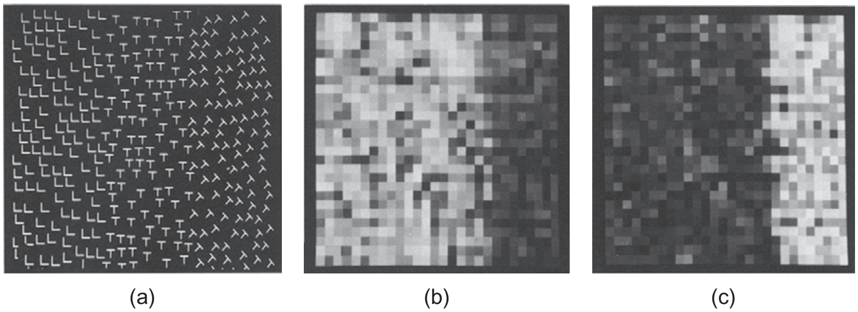


Figure 6.30 (a) The Ts and Ls in the left and middle are difficult to visually separate, but the region of rotated Ts on the right is easier to spot. (b) The output of a feature map consisting of vertical Gabors. (c) The output of a feature map consisting of oblique Gabors. (*From Turner (1986). Reproduced with permission*.)

This creates regions, each having the same general characteristics. At the final stage, boundaries are identified between regions with strongly dissimilar characteristics. This model predicts that we will divide visual space into regions according to the predominant spatial frequency and orientation information. A region with large orientation and size differences will be the most differentiated. Also, regions can be differentiated based on texture contrast. A low-contrast texture will be differentiated from a high-contrast texture with the same orientation and size components.

Figure 6.30 illustrates the Gabor segmentation theory applied to the classic perceptual conundrum. Why are the Ts and Ls difficult to distinguish? And why are they easy to distinguish when the Ts are rotated? The Gabor model accurately predicts what we see.

Tradeoffs in Information Density: An Uncertainty Principle

Daugman (1985) showed that a fundamental uncertainty principle is related to the perception of position, orientation, and size. Given a fixed number of detectors, resolution of size can be traded for resolution of orientation or position. We have shown that same principle applies to the synthesis of texture for data display when we have a data field with a high degree of spatial variation (Ware & Knight, 1995). A gain in the ability to display orientation information precisely inevitably comes at the expense of precision in displaying information through size. If size is used as a display parameter, larger elements mean that less detail can be shown.

Figure 6.31 illustrates this tradeoff, with a set of textures created with Gabor functions, although the same point applies to other primitives. Recall that a Gabor is the product

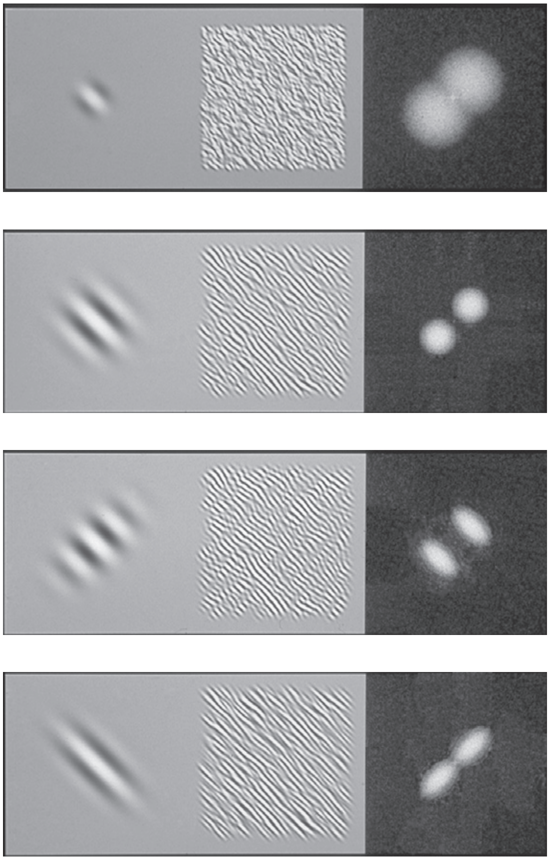


Figure 6.31 In the left-hand column are different Gabors constructed with the same sinusoidal component but with different Gaussian multipliers. The center panels show textures constructed by reducing the Gabor size by a factor of five and summing a large number using a random process. The right-hand panels show 2D Fourier transforms of the textures.

of a Gaussian envelope with a sine wave. In this figure, the textures are created by summing together a large number of randomly scattered Gabors. By changing the shape and size of the Gaussian multiplier function with the same sinusoidal grating, the tradeoff can be directly observed. When the Gaussian is large, the spatial frequency is specified quite precisely, as shown by the small image in the Fourier transform. When the Gaussian is small, position is well specified but spatial frequency is not, as shown by the large image in the Fourier transform. The lower two rows of Figure 6.31 show how the Gaussian envelope can be stretched to specify either the spatial frequency or the orientation more precisely. The implication here is that there are fundamental limits and tradeoffs related to the ways texture can be used for information display.

> **[G6.11]** Consider using texture to represent continuous map variables. This is likely to be most effective where the data varies smoothly and where surface shape features are substantially larger than texture element spacing.

Primary Perceptual Dimensions of Texture

A completely general Gabor model has parameters related to orientation, spatial frequency, phase, contrast, and the size and shape of the Gaussian envelope. However, in human neural receptive fields, the Gaussian and cosine components tend to be coupled so that low-frequency cosine components have large Gaussians and high-frequency cosine components have small Gaussians (Caelli & Moraglia, 1985). This allows us to propose a simple three-parameter model for the perception and generation of texture.

Orientation O: The orientation of the cosine component

Scale S: The size – 1/(*spatial frequency*) component

Contrast C: An amplitude or contrast component

Texture Contrast Effects

Textures can appear distorted because of contrast effects, just like the luminance contrast illusions that were described in Chapter 3. A given texture on a coarsely textured background will appear finer than the same texture on a finely textured background. This phenomenon is illustrated in Figure 6.32. The effect is predicted by higher order inhibitory connections. It will cause errors in reading data mapped to texture element size. In addition, texture orientation can cause contrast illusions in orientation, and this, too, may cause misperception of data (see Figure 6.33).

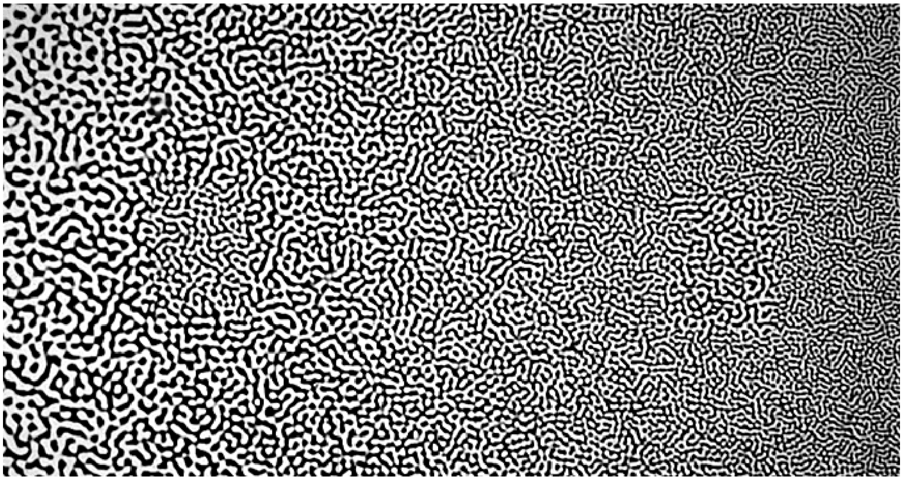


Figure 6.32 Texture contrast effect. The two patches to the left of center and the right of center have the same texture granularity, but texture contrast makes them appear different.

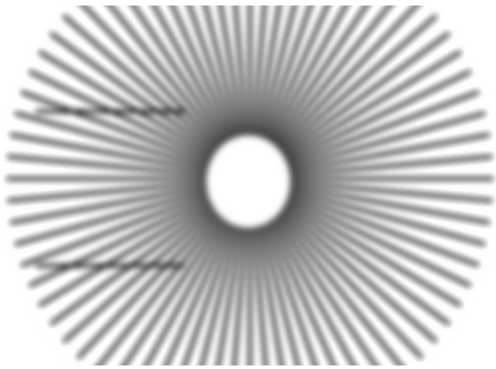


Figure 6.33 The radial texture causes the two parallel lines to the left to appear tilted.

Other Dimensions of Visual Texture

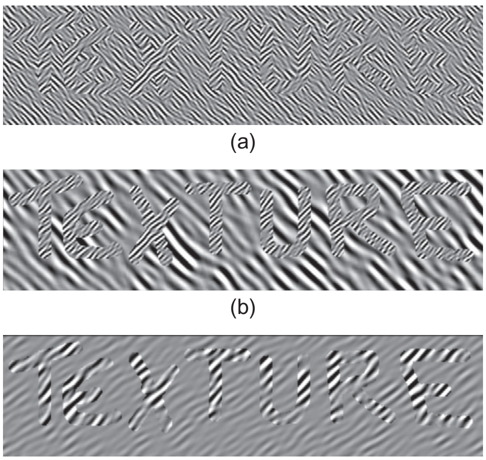
Although there is considerable evidence to suggest that orientation, size, and contrast are the three dominant dimensions of visual texture, it is clear that the world of texture is much richer than this. The dimensionality of visual texture is very high, as a visual examination of the world around us attests. Think of the textures of wood, brick, stone, fur, leather, and other natural materials. One of the important additional texture dimensions is certainly randomness (Liu & Picard, 1994). Textures that are regular have a very different quality from random ones.

Nominal Texture Codes

The most common use of texture in information display is as a nominal coding device. Geologists, for example, commonly use texture, in addition to color, in order to differentiate many different types of rock and soil. The orientation tuning of V1 neurons indicates that glyph element orientations should be separated by at least 30 degrees for a texture field of glyphs to be distinct from an adjacent texture field, and, because oriented elements will be confused with identical elements rotated through 180 degrees, fewer than six orientations can be rapidly distinguished.

Figure 6.34 shows examples of textures actually constructed using Gabor functions, randomly placed. In Figure 6.34(a), only orientation is changed among different regions of the display, and although the word TEXTURE appears distinct from its background, it is weak. The difference appears much stronger when both the spatial frequency and the orientation differ between the figure and the background, as in Figure 6.34(b). The third way that textures can be made easy to distinguish is by changing the contrast, as illustrated in Figure 6.34(c).

Of course, textures can be constructed in much more conventional ways, using stripes and dots, like the examples shown in Figure 6.35, but, still, the main key to rapid segmentation will be the spatial frequency components. This figure shows the 2D Fourier transforms of the images. The theory we have been discussing suggests that the more displayed information differs in spatial frequency and in orientation, the more distinct that information will be. The psychophysical evidence suggests that for textured regions to be visually distinct the dominant spatial frequencies should differ by at least a factor of 3, and the dominant orientations should differ by more than 30 degrees, all other factors (such as color) being equal.



(a)

(b)

(c)

Figure 6.34 The word TEXTURE is legible only because of texture differences between the letters and the background; overall luminance is held constant. (a) Only texture orientation defines the letters. (b) Orientation and size differ. (c) Texture contrast differs.

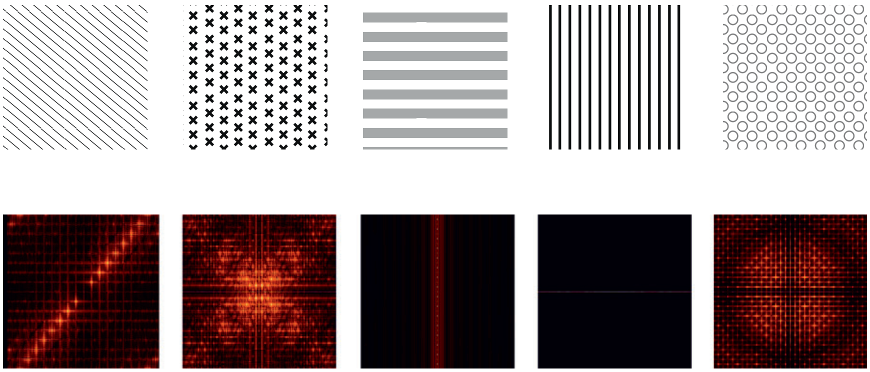


Figure 6.35 (Top row) A set of highly distinguishable textured squares, each of which differs from the others in terms of multiple spatial frequency characteristics. (Bottom row) The 2D Fourier transforms of the same textures.

[G6.12] In order to make a set of nominal coding textures distinctive, make them differ as much as possible in terms of dominant spatial frequency and orientation components. As a secondary factor, make texture elements vary in the randomness of their spacing.

The simple spatial frequency model of texture discrimination suggests that the number of textures that can be rapidly distinguished will be in the range of 12 to 24. The lower number is what we get from the product of three sizes and four orientations. When other factors, such as randomness, are taken into account, the number can be significantly larger. When we consider that in Chapter 4 we concluded that the number of rapidly distinctive color codes is fewer than 12, the use of texture clearly adds greatly to the possibility of distinctive nominal codes for areas. In addition, we can consider texture to provide a distinct channel from color, and this means that overlapping regions can be coded, as illustrated in Figure 6.14.

Using Textures for Univariate and Multivariate Map Displays

Texture can be used to display continuous scalar map information, such as temperature or pressure. The most common ways of doing this are to map a scalar variable to texture element size, spacing, or orientation. Figure 6.36 illustrates a simple texture variation using texture element size. No more than three or four steps can be reliably discriminated with such a scheme because texture elements must typically be quite small to maintain a reasonably information density, and this limits spatial channel bandwidth. Also, simultaneous contrast acting on the perceived size or orientation of texture elements can cause errors of judgment.

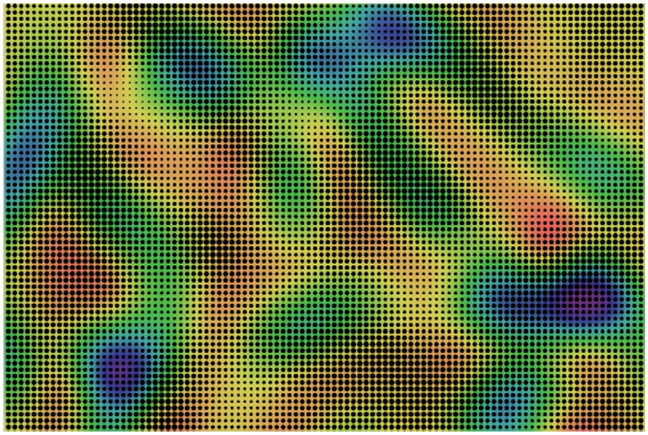


Figure 6.36 A bivariate map. One of the variables is mapped to a color sequence. The other is mapped to texture element size.

[G6.13] Use simple texture parameters, such as element size or element density, only when fewer than five ordinal steps must be reliably distinguished.

What are the prospects for encoding more than one scalar value using texture? Weigle et al. (2000) developed a technique called *oriented sliver textures* specifically designed to take advantage of the parallel processing of orientation information. Each variable in a multivariate map was mapped to a 2D array of slivers where all the slivers had the same orientation. Differently oriented 2D sliver arrays were produced for each variable. The values of each scalar map were shown by controlling the amount of contrast between the sliver and the background. Combining all of the sliver fields produced the visualization illustrated in Figure 6.37. The right-hand part of this figure shows the combination of the eight variables illustrated in the thumbnail patterns shown on the left. Weigle et al. conducted a study showing that if slivers were oriented at least 15 degrees from surrounding regions they stood out clearly; however, the experiment was only carried out with a single sliver at each location (unlike in Figure 6.37), making the task easier. To judge the effectiveness of the sliver plot for yourself, try looking for each of the thumbnail patterns in the larger combined plot. The fact that many of the patterns cannot easily be seen strongly suggests that the technique is not effective for so many variables. Also, tuning of orientation-sensitive cells suggests that slivers should be at least 30 degrees apart to be rapidly readable (Blake & Holopigan, 1985).

Another attempt to map multiple variables to texture is illustrated in Figure 6.38. In addition to glyph color, which shows temperature, texture element orientation shows the orientation and direction of the wind. Wind speed is shown using glyph area coverage. Atmospheric pressure is shown in the number of elements per unit area. This example is based on a design by Healey et al. (2008). The reader is invited to try to see how

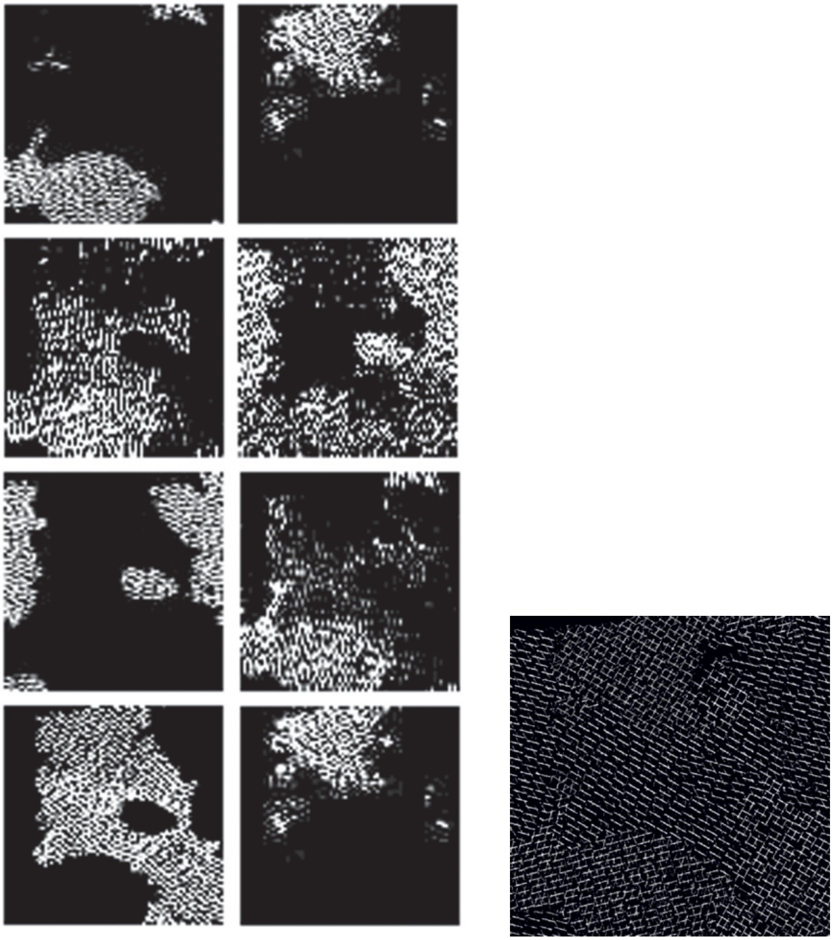


Figure 6.37 The sliver plot of Weigle et al. (2000). Each of the variables shown in the thumbnail patterns in the left part of the figure is mapped to a differently oriented sliver pattern in the combined plot. (*Courtesy of Chris Weigle*.)

many pressure levels are displayed (there are three) and where the highest winds are. Clearly, this is not an adequate solution for displaying forecast temperatures, pressures within a few millibars, or wind speeds within a few knots.

A third example of high-dimensional data display comes from Laidlaw and his collaborators (Laidlaw et al., 1998) (Figure 6.39). This was created using a very different design strategy. Rather than attempting to create a simple general technique (like slivers), the data display mapping was handcrafted in a collaboration between the scientist and the designer. Figure 6.39 shows a cross-section of a mouse spinal column. The data has seven values at each location in the image. The image is built up in layers comprised of image intensity; sampling rate, which determines the grid; elliptical

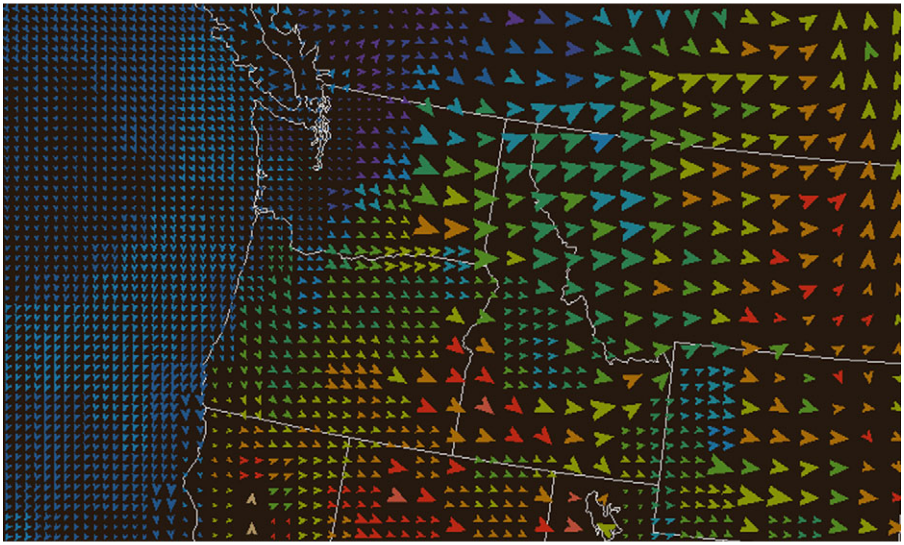


Figure 6.38 Weather patterns over the northwest continental United States. Wind orientation and direction are mapped to glyph rotation angle. Wind speed is mapped to glyph area coverage. Atmospheric pressure is mapped to density. Temperature is mapped to color.

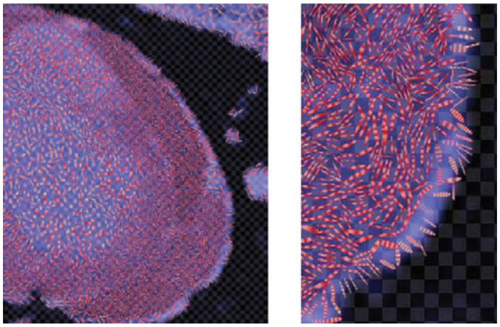


Figure 6.39 Cross-section of a mouse spinal column. Seven variables are shown at each location. Part of the image is enlarged on the right. See text for description. (*Courtesy of David Laidlaw*.)

shapes, which show the in-plane component of principal diffusion and anisotropy; and texture on the ellipses, which shows absolute diffusion rate. Without specific knowledge of mouse physiology it is impossible to judge the success of this example. Nevertheless, it provides a vivid commentary on the tradeoffs involved in trying to display high-dimensional multivariate maps. In this figure, for example, each of the elliptical glyphs is textured to display an additional variable; however, the texture striations are at right angles to the ellipse major axes, and this camouflages the glyphs, making their orientation more difficult to see. The use of texture will inevitably tend to camouflage glyph shape; if the textures are oriented, the problem will be worse. In general, the more similar the spatial frequencies of the different pattern components, the more likely they are to disrupt one another visually.

None of the preceding three examples (Figures 6.37–6.39) shows much detail. There is a good reason for this; we only have one luminance channel, and luminance variation is the only way of displaying detailed information. If we choose to use texture (or any kind of glyph field), we inevitably sacrifice the ability to show detail, because to be clear each glyph element must be displayed using luminance contrast. Larger glyphs mean that less detail can be shown.

Texture is most likely to be valuable if two scalar variables are to be displayed. In this case, we can take advantage of the fact that color and texture provide reasonably separable channels. Although, to be visible, texture necessarily consumes at least some luminance channel bandwidth. For the two-variable problem, mapping one variable to texture and another to a carefully designed color sequence can provide a reliable solution.

[G6.14] To display a bivariate scalar field, consider mapping one variable to color and a second variable to variations in texture.

Quantitative Texture Sequences

As we have observed, simultaneous contrast causes problems when using textures just as it does with color. Because the eye judges relative sizes and other properties, large errors can result and only a few steps of absolute resolution are available. But, for many visualization problems, people wish to be able to read quantitative values from a map in addition to seeing overall patterns. The displays of atmospheric pressure and temperature are two examples. Bertin (1983) suggested using a series of textures to show quantitative values. I further developed the idea of using a carefully calibrated sequence of texture elements, each of which is monotonically lighter or darker than the previous, in order to show both quantity and form in a data set (Ware, 2009). Figure 6.40 shows an example of a 10-step sequence of texture overlaid on a map of color variation. Figure 6.41 shows a more complex example that has 14 texture steps visible, showing atmospheric pressure. This example actually uses three different perceptual channels. Motion is used for wind speed and direction, quantitative texture sequences are used for pressure, and a color sequence is used for temperature.

[G6.15] To design textures so that quantitative values can be reliably judged, use a sequence of textures that are both visually ordered (for example, by element size or density) and designed so that each member of the sequence is distinct from the previous one in some low-level property.

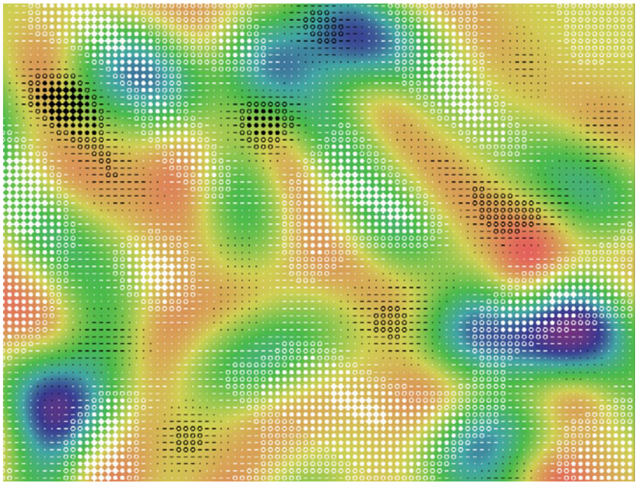


Figure 6.40 A carefully designed 10-step sequence of textures shows one variable, and a color sequence shows a second.

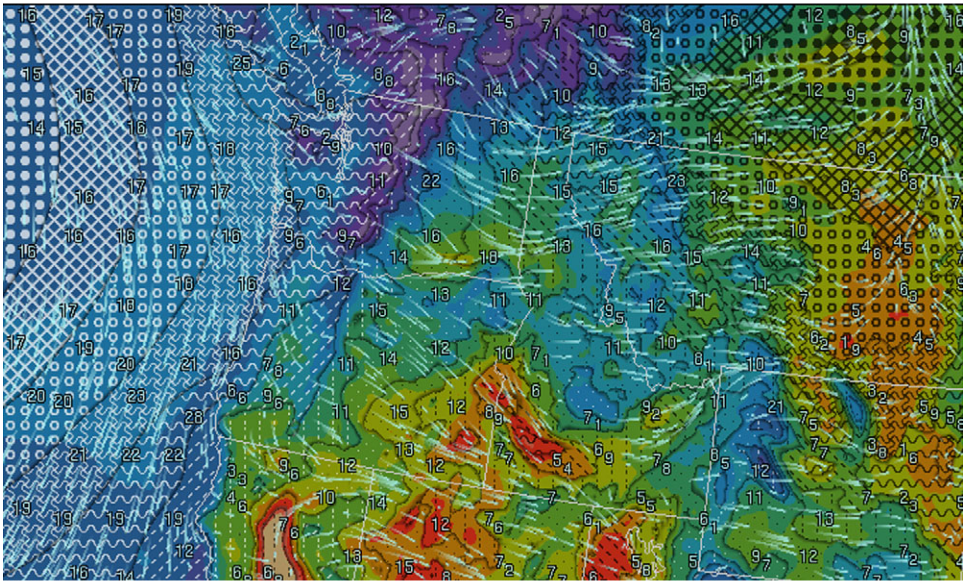


Figure 6.41 In this weather map, temperature is mapped to color. Pressure is mapped to a sequence of 14 textures. Wind orientation and direction are given using *animated* streaklets, and wind speed is displayed using the animation speed as well as numbers. Compare with the same data in Figure 6.38.

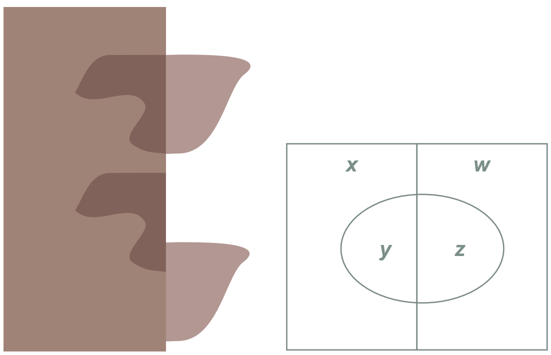
Perception of Transparency: Overlapping Data

In many visualization problems, it is desirable to present data in a layered form. This is especially common in geographic information systems (GISs). So that the contents of different layers are simultaneously visible, a useful technique is to present one layer of data transparently over another; however, there are many perceptual pitfalls in doing this. The contents of the different layers will always interfere with each other to some extent, and sometimes the two layers will fuse perceptually so that it is impossible to determine to which layer a given object belongs.

In simple displays, as in Figure 6.42(a), the two main determinants of perceived transparency are good continuity (Beck & Ivry, 1988) and the ratio of colors or gray values in the different pattern elements. A reasonably robust rule for transparency to be perceived is $x < y < z$ or $x > y > z$ or $y < z < w$ or $y > z > w$, where x, y, z, and w refer to gray values arranged in the pattern shown in Figure 6.42(b) (Masin, 1997). Readers who are interested in perceptual rules of transparency should consult Metelli (1974).

One possible application of transparency in user interfaces is to make pop-up menus transparent so that they do not interfere with information located behind them. Harrison and Vincente (1996) investigated the interference between background patterns and foreground transparent menus. They found that it took longer to read from the menu with text or wireframe drawings in the background than with continuously shaded images in the background. This is exactly what would be expected from an interference model. Because a continuously shaded image lacks the high spatial frequency detail of a wireframe image or text, there will be less interference between the two.

Another way to represent layers of data is to show each layer as a see-through texture or screen pattern (Figure 6.43). Watanabe and Cavanaugh (1996) explored the conditions under which people perceive two distinct overlapping layers, as opposed to a single fused composite texture. They called the effect *laciness*. In Figure 6.43(a) and



(a) (b)

Figure 6.42 In (a) transparency depends both on the color relationships and on good continuity. (b) See text for transparency rules.

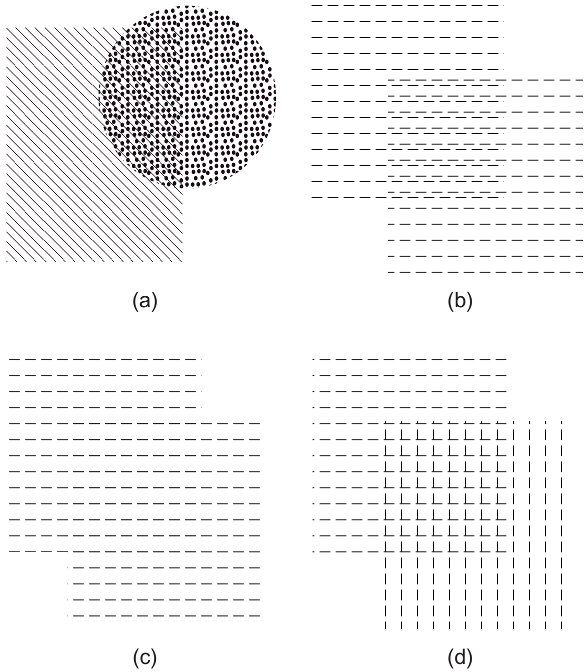


Figure 6.43 Watanabe and Cavanaugh (1996) called the texture equivalency of transparency *laciness*. This figure is based on their work.

Figure 6.43(b), two different overlapping shapes are clearly seen, but in Figure 6.43(c), only a single textured patch is perceived. In Figure 6.43(d), the percept is bistable. Sometimes it looks like two overlapping squares containing patterns of "—" elements, and sometimes a central square containing a pattern of "+" elements seems to stand out as a distinct region.

In general, when we present layered data, we can expect the basic rules of perceptual interference, discussed in Chapter 5, to apply. Similar patterns interfere with one another. The problem with Figure 6.43(c) is one of aliasing. Graphical patterns that are similar in terms of color, spatial frequency, motion, and so on tend to interfere more (and fuse more) with one another than do those with dissimilar components.

[G6.16] When using overlapping textures to separate overlapping regions in a display, avoid patterns that can lead to aliasing problems when they are combined.

[G6.17] When using textures in combination with background colors for overlapping regions, choose lacy textures so that other data can be perceived through the gaps.

Because texture elements are small by definition, luminance contrast is needed to make them distinct from the background. When texture is layered transparently over other color-coded data, it is important that luminance contrast with the background coding exists; otherwise, the texture elements will not be visible. This constrains both the colors used in constructing the texture elements and the colors that can be used in the background. The easiest solution is to make the texture elements either black or white and to restrict the set of background colors so that they do not occupy either the low luminance or the high luminance end of the range, respectively.

[G6.18] When using lacy textures in combination with colors for overlapping regions, ensure luminance contrast between texture elements in the foreground and color-coded data presented in the background.

Perceiving Patterns in Multidimensional Discrete Data

One of the most interesting but difficult challenges for data visualization is to support the exploratory data analysis of discrete multidimensional data. Visualization can be a powerful tool in data mining, in which the goal is often a kind of general search for relationships and data trends. For example, marketing experts often collect large amounts of data about individuals in potential target populations. The variables that are collected might include age, income, educational level, employment category, tendency to purchase chocolate, and so on. Each of the measured variables can be thought of as a data dimension. If the marketer can identify clusters of values in this multidimensional data set related to the likelihood of purchasing different products, this can result in better targeted, more effective advertising. The task of finding particular market segments is one of finding distinct clusters in the multidimensional space that is formed by many variables.

Sometimes a scientist or a data analyst approaches data with no particular theory to test. The goal is to explore the data for meaningful and useful information in masses of mostly meaningless numbers. Plotting techniques have long been tools of the data explorer. In essence, the process is to plot the data, look for a pattern, and interpret the findings, so the critical step in the discovery process is an act of perception. The four scatterplots in Figure 6.44 illustrate very different kinds of data relationships. In the first, there are two distinct clusters, perhaps suggesting distinct subpopulations of biological organisms. In the second, there is a clear negative linear relationship between two measured variables. In the third, there is a curvilinear, inverted U-shaped relationship. In the fourth, there is an abrupt discontinuity. Each of these patterns will lead to a very different hypothesis about underlying causal relationships between the variables. If any of the relationships were previously unknown, the researcher would be rewarded with a discovery. It would be very difficult to see the patterns by scrutinizing tables of numbers. The power of a visualization method

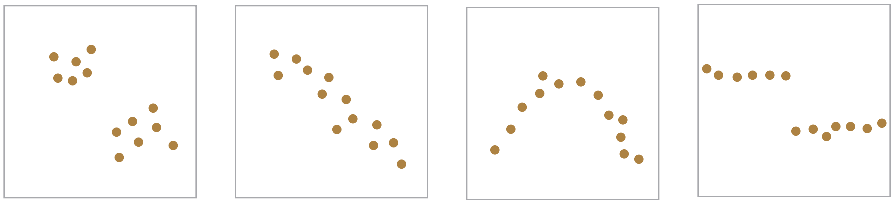


Figure 6.44 The scatterplot is an essential tool when looking for pattern in discrete data having two quantitative attributes.

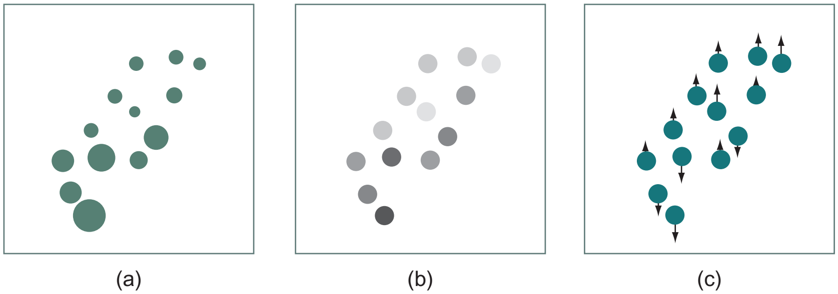
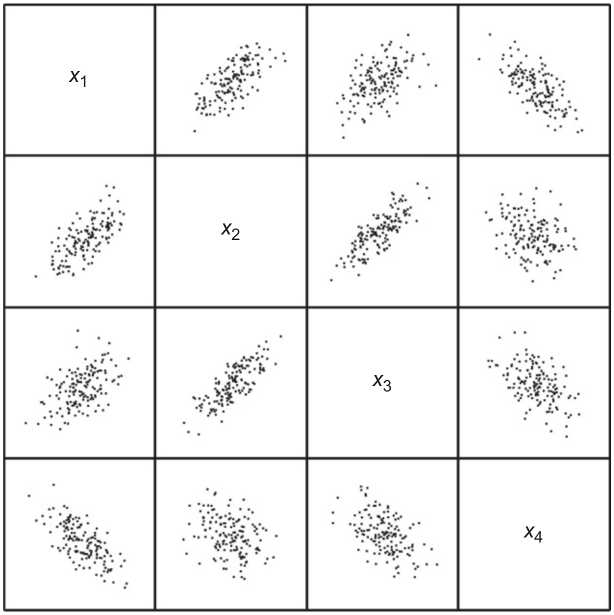


Figure 6.45 Three-dimensional discrete data. The third dimension is given by (a) point size, (b) gray value, and (c) phase of oscillatory point motion.

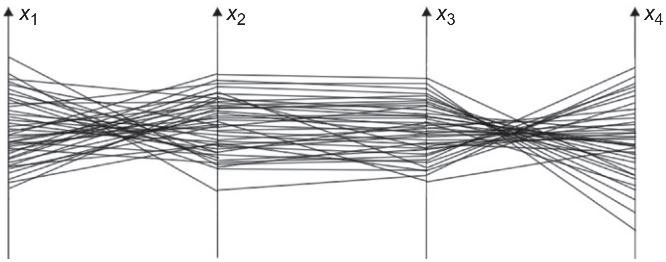
comes from enabling people to see patterns in noisy data or, in other words, letting them see meaningful signals in noise.

Of course, there is an infinite variety of different meaningful patterns that may be found in data, and what is a signal in one context may be noise in another. But there are two particular kinds of patterns that are very commonly of interest: *clusters* and *correlations*. Examples are shown in the first two boxes of Figure 6.44. Conventional scatterplots like these are probably the best solution when each data point has two attributes. The problem gets more difficult when more than two numerical attributes are involved. For four attributes, it is common to add glyph size and color (Figure 6.45). Limoges et al. (1989) investigated glyph size, gray value, and the *phase* of oscillatory motion as a way of displaying correlations and found that subjects were most sensitive to phase differences. Nevertheless, the use of color and/or point size is well established as a method for representing three- or four-dimensional discrete data in scatterplots.

What do we do about data with more than three dimensions? One solution for higher dimensional discrete data display is the generalized draftman's plot (Chambers et al., 1983). In this technique, all pairs of variables are used to create a set of 2D scatterplots. An example, from Li et al. (2010), is shown in Figure 6.46. Although the generalized drafter's plot can often be useful, it suffers from a disadvantage in that it is very difficult



(a)



(b)

Figure 6.46 (a) Four-dimensional discrete data displayed using a generalized draftsman's plot. (b) The same data displayed using a parallel coordinates plot. (*From Li et al. (2010). Reproduced with permission*.)

to see higher dimensional data patterns that can be understood only when three or more data dimensions are simultaneously taken into account.

A second solution is the parallel coordinates plot (Inselberg & Dimsdale, 1990). In a parallel coordinates plot, each attribute dimension is represented by a vertical line, as shown in Figure 6.46(b) and Figure 6.47. The data points become lines that connect the various attribute values.

One of the problems with the parallel coordinates plot is that the patterns that are seen depend on the way the axes are ordered with respect to one another. It is much easier to see relationships between variables that have adjacent axes; permuting the order of the

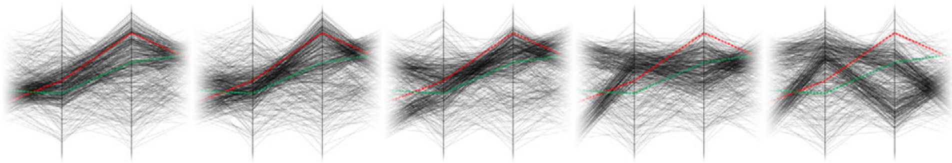


Figure 6.47 Parallel coordinates plot with permuted axes. (*From Holten & van Wijk (2010). Reproduced with permission*.)

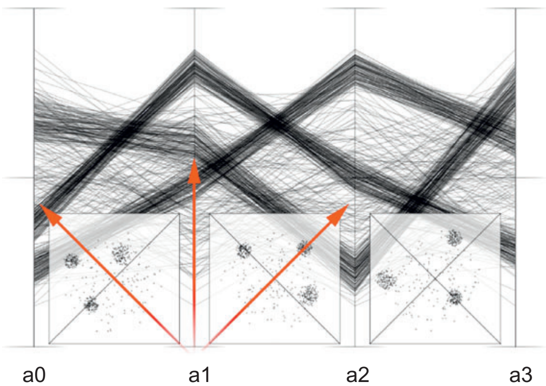


Figure 6.48 A parallel coordinates plot with embedded scatterplots. (*From Holten & van Wijk (2010). Reproduced with permission*.)

axes changes the patterns that are seen. Figure 6.47 shows views of a data set in a series of plots where the axes have been permuted in a so-called random tour. In certain arrangements, particularly the one on the right, the clusters are much more distinctive.

In a study of subjects' ability to see clusters in multidimensional discrete data using parallel coordinates plots, Holten and van Wijk (2010) found that a version with embedded scatterplots was the clear winner, both in terms of correctness and speed of response (Figure 6.48). This leads one to suspect that a generalized draftsman's plot would have performed best without the parallel coordinates. A generalized draftsman's plot is a set of 2D scatterplots that shows all pairwise combinations of dimensions.

Another investigation compared scatterplots with generalized draftsman's plots in terms of how well they allowed subjects to see correlations between variables (Li, Martens, & van Wijk, 2010). Again, the more conventional scatterplot was found to be considerably more effective than the generalized draftsman's plot.

It is important to recognize, though, that parallel coordinates plots are intended to be used with an interactive technique called *brushing*. With brushing, a range on one of the axes is selected, causing the polylines passing through that range to become

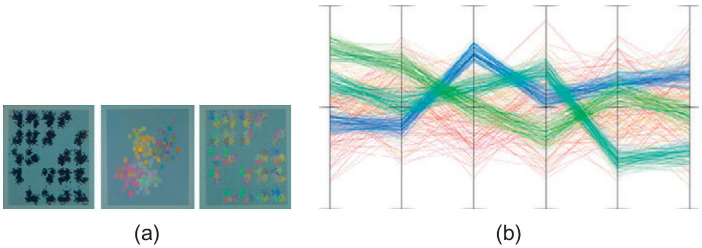


Figure 6.49 (a) Color-enhanced generalized draftsman's plot. (*From Ware & Beatty (1988). Reproduced with permission.*) (b) Color-enhanced parallel coordinates plot using a method designed to help bring out clusters. (*From Holten & van Wijk (2010). Reproduced with permission.*)

highlighted in some way. This makes the method become part of an exploratory process, where the instantaneous view may be less important; however, brushing can also be applied to generalized draftsman's plots, so this is not a unique advantage.

Color mapping can be used to extend the number of displayable data dimensions to five in a single scatterplot, as shown in Figure 6.49(a). Ware and Beatty (1988) developed a simple scheme for doing this. The technique is to create a scatterplot in which each point is a colored patch rather than a black point on a white background. Up to five data variables can be mapped and displayed as follows:

Variable 1 → x-axis position

Variable 2 → y-axis position

Variable 3 → amount of red

Variable 4 → amount of green

Variable 5 → amount of blue

In an evaluation of cluster perception in this kind of display, Ware and Beatty (1988) concluded that color display dimensions could be as effective as spatial dimensions in allowing the visual system to perceive clusters. For this task, at least, the technique produced an effective five-dimensional window into the data space, but there are drawbacks to this kind of color-mapped scatterplot. Although identifying clusters and other patterns can be easy, interpreting them can be difficult. A cluster may appear greenish because it is low on the red variable or high on the green variable. It can be difficult to distinguish the two. The use of color can help us to identify the presence of multidimensional clusters and trends, but once the presence of these trends has been determined, other methods are needed to analyze them.

Color can also be used to enhance parallel coordinates plots as well as scatterplots. Figure 6.49(b) shows an example from Holten and van Wijk, using a coloring method designed specifically to enhance the perception of clusters.

Taken together, the empirical results suggest that patterns are more readily perceived using a generalized draftsman's set of scatterplots than using parallel coordinates.

[G6.19] To display discrete data with more than four dimensions, consider using color-enhanced generalized draftsman's plots in combination with brushing.

Pattern Learning

If pattern perception is, as claimed, fundamental to extraction of meaning from visualizations, then an important question arises: Can we learn to see patterns better? Artists talk about seeing things that the rest of us cannot see, and ace detectives presumably spot visual clues that are invisible to the beat officer. What is the scientific evidence that people can learn to see patterns better? The results are mixed. There have been some studies of pattern learning where almost no learning occurred; an often-cited example is the visual search for the simple conjunction of features such as color and shape (Treisman & Gelade, 1980). Other studies, however, have found that learning does occur for certain types of patterns (Logan, 1994). A plausible way of reconciling the differences in results is that pattern learning occurs least for simple, basic patterns processed early in the visual system and most for complex, unfamiliar patterns processed late in the visual system. Fine and Jacobs (2002) reviewed 16 different pattern learning experiments and found very different amounts of learning. The studies they looked at all contained large numbers of trials (in which a subject would attempt to see a particular pattern in a display) distributed over several days. They found that for simple pattern-perception tasks, such as the ability to resolve a grating pattern like that shown in Figure 6.50(a), almost no learning occurred. This task depends on early-stage visual processing, for which the neural machinery is consolidated in the first few months of life. In tasks involving patterns of intermediate complexity, some learning did occur; for example, people could eventually learn to perceive spatial frequency differences within a pattern such as that shown in Figure 6.50(b). This is a "plaid" pattern constructed by summing a variety of the sinusoidal gratings. Processing of such patterns is thought to occur mostly at an intermediate stage of the visual system. The most learning was found in higher

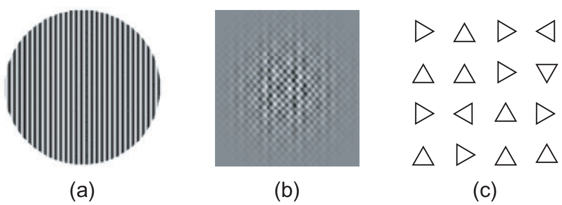


Figure 6.50 Three patterns used in perceptual learning studies.

level pattern tasks, such as detecting the downward pointing triangles in Figure 6.50(c) (Sigman & Gilbert, 2000).

Another factor that affects learning is the degree to which a particular pattern is already familiar. We would not expect much change in a subject's ability to identify letters of the alphabet in a short experiment, because most people have already been exposed to millions of alphabetic characters. Rapid learning can only be expected for patterns that are unfamiliar. The change in rate of learning over time is captured by the *power law of practice*, which has the following form:

$$\log(T_n) = C - \alpha \log(n) \tag{6.1}$$

This law states that the log of the time to respond on the nth trial (T_n) is inversely proportional to the log of the number of trials. The constant C is the time taken on the first trial (or block of trials).

The *power law of practice* is usually applied to manual skill learning, but it has also been shown to apply to the perception of complex patterns. Kolers (1975) found that the power law applied to the task of learning to read inverted text. His results are illustrated in Figure 6.51. Initially, it took subjects about 15 minutes to read a single inverted page, but when over 100 pages had been read, the time was reduced to 2 minutes. Although Figure 6.50 shows a straight-line relationship between practice and learning, this is only because of the logarithmic transformation of the data. The relationship is actually very nonlinear. Consider a hypothetical task where people improve by 30% from the first day's practice to the second day. Doubling the amount of practice has resulted in a 30% gain. According to the power law, someone with 10 years of experience at the same task will require a further 10 years to improve by 30%. In other words, practice yields decreasing gains over time.

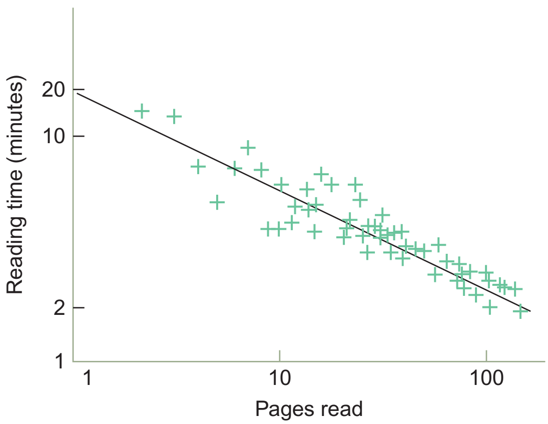


Figure 6.51 The time to read a page of inverted text is plotted against the number of pages read (Kolers, 1975). Both axes have logarithmic spacing. (*Data replotted from Newell & Rosenbloom (1981)*.)

Priming

In addition to long-term pattern-learning skills, there are also *priming* effects that are much more transient. Whether these constitute learning is still the subject of debate. Priming refers to the phenomenon that, once a particular pattern has been recognized, it will be much easier to identify in the next few minutes or even hours, and sometimes days. This is usually thought of as a kind of heightened receptivity within the visual system, but some theorists consider it to be visual learning. In either case, once a neural pathway has been activated, its future activation becomes facilitated. For a modern theory of perceptual priming based on neural mechanisms, see Huber and O'Reilly (2003).

What are the implications of these findings for visualization? One is that people can learn pattern-detection skills, although the ease of gaining these skills will depend on the specific nature of the patterns involved. Experts do indeed have special expertise. The radiologist interpreting an X-ray, the meteorologist interpreting radar, and the statistician interpreting a scatterplot will each bring a differently tuned visual system to bear on his or her particular problem. People who work with visualizations must learn the skill of seeing particular kinds of patterns in data that relate to analytic tasks, for example, finding a cancerous growth. In terms of making visualizations that contain easily identified patterns, one strategy is to rely on pattern-finding skills that are common to everyone. These can be based on low-level perceptual capabilities, such as seeing the connections between objects linked by lines. We can also rely on skill transfer. If we know that our users are cartographers, already good at reading terrain contour maps, we can display other information, such as energy fields, in the form of contour maps. The evidence from priming studies suggests that when we want people to see particular patterns, even familiar ones, it is a good idea to show them a few examples ahead of time.

One of the main implications of perceptual learning was already stated in a guideline that was given in Chapter 1: [G1.4] *Graphical symbol systems should be standardized within and across applications*. This can be restated in terms of patterns.

> **[G6.20]** Make every effort to standardize the mapping of data to visual patterns within and across applications.

Vigilance

Sometimes people must search for faint and rarely occurring targets. The invention of radar during World War II created a need for radar operators to monitor screens for long hours, searching for visual signals representing incoming enemy aircraft. This led to research aimed at understanding how people can maintain vigilance while performing monotonous tasks. This kind of task is common to airport baggage X-ray screeners, industrial quality-control inspectors, and the operators of large power grids. Vigilance tasks commonly involve visual targets, although they can be auditory. There is extensive literature concerning vigilance (for reviews, see Davies &

Parasuraman, 1980; Wickens, 1992). Here is an overview of some of the more general findings.

1. Vigilance performance falls substantially over the first hour.
2. Fatigue has a large negative influence on vigilance.
3. To perform a difficult vigilance task effectively requires a high level of sustained attention, using significant cognitive resources. This means that dual tasking is not an option during an important vigilance task. It is not possible for operators to perform some useful task in their "spare time" while simultaneously monitoring for some signal that is difficult to perceive.
4. Irrelevant signals reduce performance. The more irrelevant visual information presented to a person performing a vigilance task, the more difficult the task becomes.
5. The difficulty of seeing targets varies inversely with target frequency. People are more than twice as likely to see frequent targets than rare ones (Wolfe et al., 2007).

Overall, people perform poorly on vigilance tasks, but there are a number of techniques that can improve performance. One method is to provide reminders at frequent intervals about what the targets will look like. This is especially important if there are many different kinds of targets. Another is to take advantage of the visual system's sensitivity to motion. A difficult target for a radar operator might be a slowly moving ship embedded in a great many irrelevant noise signals. Scanlan (1975) showed that if a number of radar images are stored up and rapidly replayed, the image of the moving ship can easily be differentiated from the visual noise. Generally, anything that can transfer the visual signal into the optimal spatial or temporal range of the visual system should help detection. If the signal can be made perceptually different or distinct from irrelevant information, this will also help. The various factors that make color, motion, and texture distinct can all be applied.

Wolfe et al. (2007) found a method for counteracting the infrequent target effect. In a task that closely approximated airport screening, they showed that inserting retraining sessions into the work schedule improved detection rates considerably. These sessions contained bursts of artificially *frequent* targets with *feedback* regarding correctness of detection.

[G6.21] In search tasks for infrequent targets, insert retraining sessions during which targets are frequent and feedback is given regarding success or failure.

The Visual Grammar of Node–Link Diagrams

Diagrams are always hybrids of the conventional and the perceptual. Diagrams contain conventional elements, such as abstract labeling codes, that are difficult to learn but formally powerful. They also contain information that is coded according to perceptual rules, such as Gestalt principles. Arbitrary mappings may be useful, as in the case of mathematical notation, but a good diagram takes advantage of basic

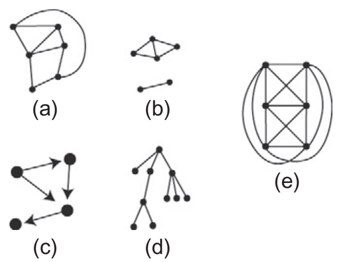


Figure 6.52 Node–link diagrams, technically called *graphs*: (a) A graph. (b) A graph with two connected components. (c) A directed graph. (d) A tree structure graph. (e) A nonplanar graph; it cannot be laid out on a plane without links crossing.

perceptual mechanisms that have evolved to perceive structure in the environment. By presenting examples, the following sections describe the visual grammar of two different kinds of diagrams: node–link diagrams and the layered maps used in GISs.

For a mathematician, a graph is a structure consisting of nodes and edges (links between the nodes). See Figure 6.52 for examples. There is a specialized academic field called *graph drawing* dedicated to making graphs that are pleasantly laid out and easy to read. In graph drawing, layout algorithms are optimized according to aesthetic rules, such as the minimization of link crossings, displaying symmetry of structure, and minimizing bends in links (Di Battista et al., 1998). Path bendiness and the number of link crossings have both been shown empirically to degrade performance on the task of finding the shortest path between two nodes (Ware et al., 2002). For the most part, however, there has been little attempt either to systematically apply our knowledge of pattern perception to problems in graph drawing or to use empirical methods to determine that graphs laid out according to aesthetic principles are, in fact, easier to understand.

In the following paragraphs, we broaden the concept of a graph to consider a very large class of diagrams that we will call, generically, *node–link diagrams*. The essential characteristic of these diagrams is that they consist of *nodes*, representing various kinds of entities, and *links*, representing relationships between the entities. Dozens of different diagrams have this basic form, including software structure diagrams, data-flow diagrams, organization charts, and software modeling diagrams. Figure 6.53 provides four examples commonly used in software engineering. The set of abstractions common to node–link diagrams is so close to ubiquitous that it can be called a *visual grammar*. Entities are almost always shown using outline boxes, circles, or small symbols. The connecting lines generally represent different kinds of relationships, transitions, or communication paths between nodes.

The various reasons why we may be justified in referring to these graphical codes as *perceptual* are distributed throughout this book, but are addressed mostly in this chapter and Chapter 5. The fundamental argument is that closed contours are basic in defining visual objects. Thus, although a circular line may be only a mark drawn on paper, at some level in the visual system it is *objectlike*. Similarly, two objects can be connected

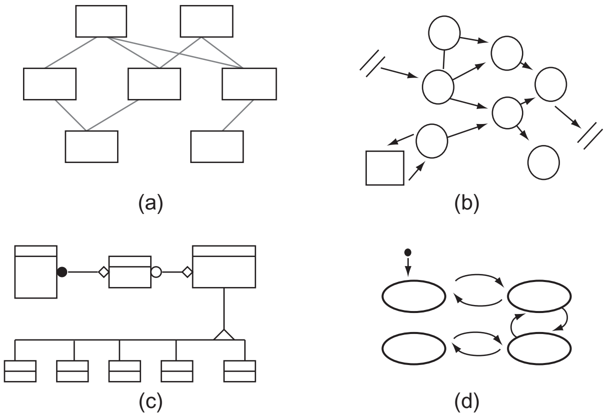


Figure 6.53 Four different kinds of node–link diagrams used in software engineering: (a) A code module diagram. (b) A data flow diagram. (c) An object modeling diagram. (d) A state-transition diagram. Each of these diagrams would normally contain text labels on the nodes and the arcs.

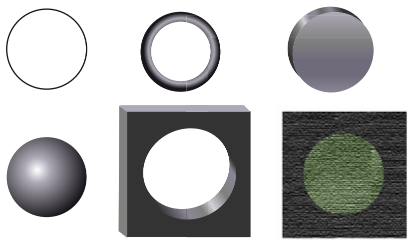


Figure 6.54 The line circle shown at the top left can represent many kinds of objects: a wire ring, a disk, a ball, a cut-out hole, or the boundary between regions of different color. More importantly, it can represent abstract concepts relating to objects.

by a line, and this visual connection has the ability to represent any of a number of relationships. The likely explanation for why nodes represent entities so well and linking lines represent relationships so well is that there are deep metaphors, based on sensory perception of the world, that provide a scaffolding for even our most abstract concepts (Lakoff & Johnson, 1980; Pinker, 2007).

Although lines get their expressive power from neural mechanisms designed to interpret objects, they are fundamentally ambiguous. Kennedy (1974) elucidated several ways in which contours (lines) can represent aspects of the environment. Some of them are illustrated in Figure 6.54. A circle can represent a ring, a flat disk, a ball, a hole, or the boundary between two objects (a disk in a hole). This nicely illustrates the mixture of perception and convention that is common to diagrams. Our visual systems are capable of interpreting a line contour in any of these ways. In real-world scenes, additional information is available to clarify ambiguous contours. In a diagram, the contour may remain perceptually ambiguous, and some convention may be necessary to remove the ambiguity. In one kind of diagram, a circle may represent an object; in another, it may represent a hole; in a third, it may represent the boundary of a geographic region. The diagram convention, the context, and the Gestalt factors tells us which interpretation is correct, but contours are not subject to an infinite number of interpretations. Their power comes from the small set of general meanings that they support through deep perceptual analogies.

Generally, though, the Gestalt figure–ground rules tell us that small, closed regions are likely to be seen as figures, or in other words, as objectlike. Looking ahead to the next chapter, we find theories suggesting that attributes such as color, shape, and size are mostly perceived as secondary attributes of objects.

> **[G6.22]** When developing glyphs, use small, closed shapes to represent data entities, and use the color, shape, and size of those shapes to represent attributes of those entities.

Figure 6.55 provides a number of examples illustrating this guideline.

A general data model that uses a form of node–link diagram is the entity–relationship model. It is widely used in computer science and business modeling (Chen, 1976). In entity–relationship modeling, entities can be objects and parts of objects, or more abstract things such as parts of organizations. Relationships are the various kinds of connections that can exist between entities (notice the metaphor in the use of the word *connection*). For example, an entity representing a wheel will have a part-of relationship to an entity representing an automobile. A person may have a customer relationship to a store. Both entities and relationships can have attributes. Thus, a particular customer might be a preferred customer. An attribute of an organization might be the number of

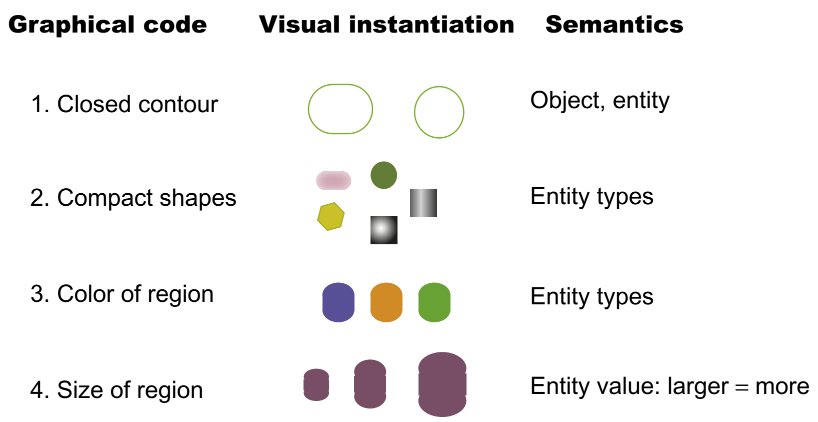


Figure 6.55 The basic visual grammar of entity representations for node–link diagrams.

its employees. There are standard diagrams for use in entity–relationship modeling, but we are not concerned with these here. We are more interested in the different ways diagrams can be constructed to represent entities, relationships, and attributes in an easily perceived manner.

The vast majority of node–link diagrams currently in use are very simple. For the most part, these diagrams use identical rectangular or circular nodes and constant width lines, like those shown in Figure 6.56. Although such generic diagrams are

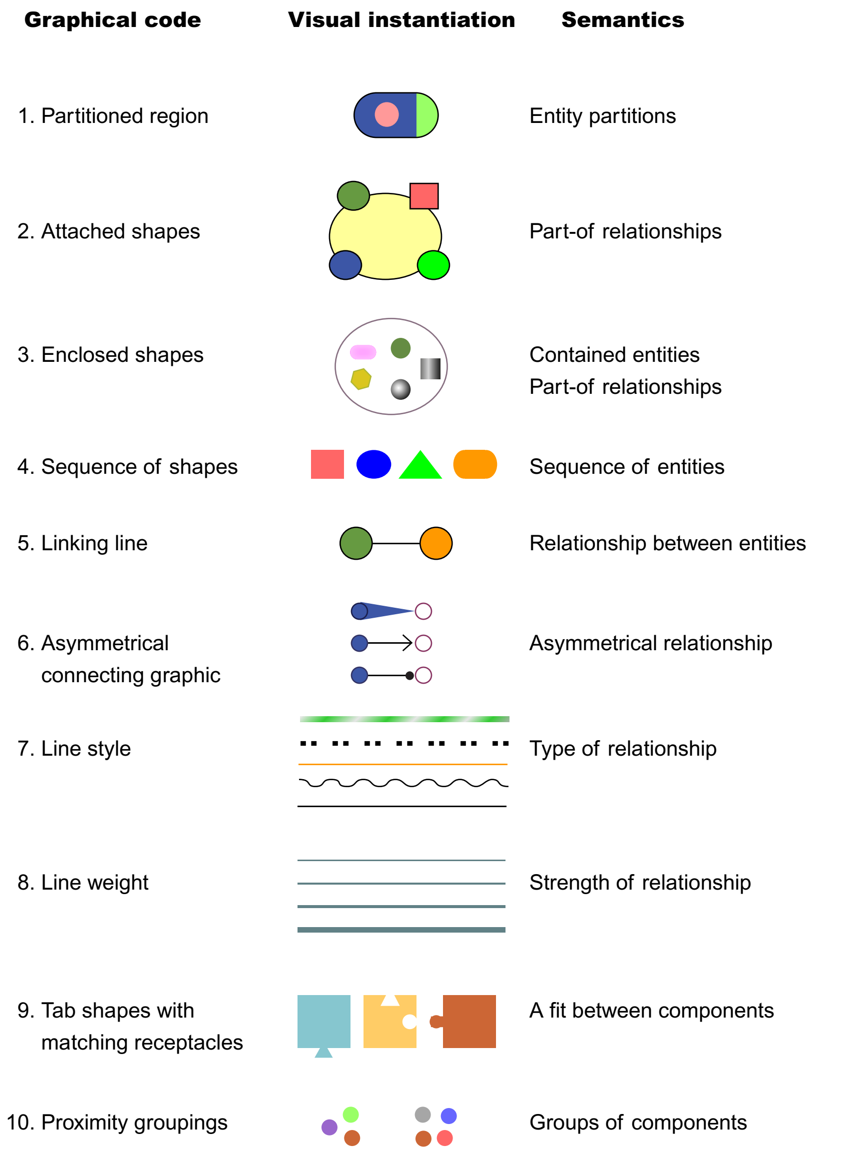


Figure 6.56 The visual grammar of relationship representations.

very effective in conveying patterns of structural relationships among entities, they are often poor at showing the types of entities and the types of relationships. Attributes, when they are shown, are often provided in the form of text labels attached to the boxes and lines, although occasionally dashed lines and other variations are used to denote types. As Figure 6.44 suggests, a great variety of graphical styles can be used to enrich diagrams and express attributes of both entities and relationships.

The visual metaphors embedded in language, in words such as *connection*, *linkage*, *attachment*, or *part-of*, suggest ways of graphically encoding relationships between entities. According to Pinker (2007), such metaphors are not embellishments to language, but reflect the basic structure of thought.

[G6.23] Use connecting lines, enclosure, grouping, and attachment to represent relationships between entities. The shape, color, and thickness of lines and enclosures can represent the types of relationships.

Figure 6.56 shows examples of graphical methods for defining relationships. Most of these methods are only useful for symmetric relationships, but in fact most relationships between entities are not symmetrical. One entity *controls* another in some way, or is *used by* another, or is *part of* another. A graph that shows asymmetric relationships is called *directed*, and a standardized convention that shows the asymmetry is a line with an arrowhead at one end. In a recent study, Holten and van Wijk (2009) showed that a better alternative exists, as illustrated in Figure 6.57. The version using the tapered lines made it significantly easier to trace relationships compared to the use of conventional arrows. A theory that explains why this may be superior is based on a concept of attention spreading along contours (Houtkamp et al., 2003). From a given node, activation should tend to spread more readily along lines that start out thick than lines that start out thin.

[G6.24] As an alternative to arrows to represent directed relationships in diagrams, consider using tapered lines with the broadest end at the source node.

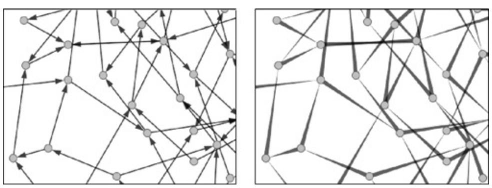


Figure 6.57 Two methods for representing directed relationships in a diagram. Research suggests that the one on the right can be interpreted more rapidly. (*From Holten & van Wijk (2009). Reproduced with permission*.)

The Visual Grammar of Maps

A second visual grammar can be found in the way maps are designed and interpreted. As with node–link diagrams, we rely on strong visual metaphors, although in this case they are used to reason about geographical space. The terms *enclosure*, *path*, *region*, *overlap*, and *connection* all have visual expressions. Only three basic kinds of graphical marks are common to most maps: areas, line features, and small symbols (Mark & Franck, 1996). Figure 6.58 elaborates the basic grammar of maps and shows how areas, lines, or small symbols can work in isolation and in combination.

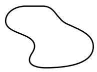
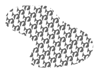
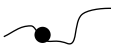
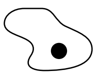
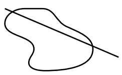
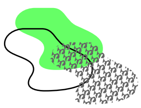
Graphical code	Graphical representation	Semantics
1. Closed contour		Geographic region
2. Colored region		Geographic region
3. Textured region		Geographic region
4. Line		Linear feature such as a river or road, depends on scale
5. Dot		Point feature such as a town, depends on scale
6. Dot on line		Point feature such as a town connected by linear feature such as a road
7. Dot in closed contour or other graphical region		Point feature such as a town located within a geographic region
8. Line crossed graphical region		Linear feature such as a road crossing a geographic region
9. Line exits graphical region		Linear feature such as a river originates in a geographic region
10. Overlapping graphical regions		Overlapping geographical regions

Figure 6.58 The basic visual grammar of map elements.

1, 2, 3. Geographical areas are usually denoted by closed contours, tinted areas, or textured areas. Often all three methods can be used—for example, lines to represent county boundaries, color coding to represent climate, and texture to represent vegetation.

4. Geographical linear features represent either boundaries or elongated geographical regions. The difference between geographical areas and linear features is sometimes related to scale. On a small scale, a river will be represented by a thin line of constant width; on a larger scale, it can become an extended geographical area.
5. Dots or other small symbols are used to represent point features, although whether or not something is a point feature depends on the scale. On a large scale, an entire city may be represented by a single dot; on a small scale, a dot might be used to show the locations of churches, schools, or tourist attractions.
6. A dot on a line means that the entity denoted by the point feature is on, or attached to, the entity denoted by the linear feature; for example, a city is "on" a river.
7. A dot within a closed contour means that the entity denoted by the point feature lies within the boundaries of the area feature; for example, a town is within a province.
8. A line crossing a closed contour region means that a linear feature crosses an area feature; for example, a road passes through a county.
9. A line that ends in a closed-contour region means that a linear feature ends or starts within an area feature; for example, a river flows out of a park.
10. Overlapping contour regions defined by contour, color, or texture denote overlapping spatial regions; for example, a forested region may overlap a county boundary.

[G6.25] Use closed contours, areas of texture, or areas of color to denote geographic regions. Use color, texture, or boundary style to denote the type of region.

[G6.26] Use lines to represent paths and linear geographic features. Use line color and style to represent the type of linear feature.

[G6.27] Use small, closed shapes to represent point entities, such as cities, that appear small on a map. Use color, shape, and size to represent attributes of these entities.

Maps need not be used only for geographical information. Johnson and Shneiderman (1991) developed a visualization technique they called a *treemap*, for displaying information about the tree data structures commonly used in computer science. Figure 6.59 shows an example of a tree data structure presented in treemap form and in a conventional node–link diagram.

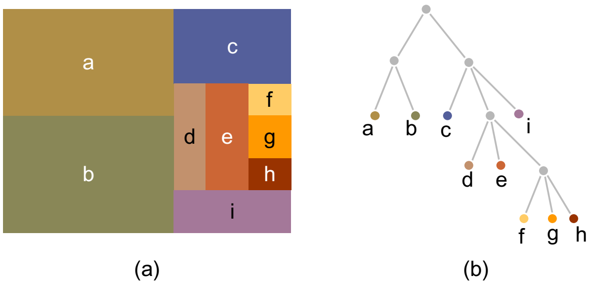


Figure 6.59 (a) A treemap representation of hierarchical data. Areas represent the amount of data stored in the tree data structure. (b) The same tree structure, represented using a conventional node–link diagram.

The original treemap was based on the following algorithm. First, the rectangle is divided with a vertical partition according to the number of branches from the base of the tree. Next, each subrectangle is similarly divided, but with horizontal partitions. This process is repeated to the leaves of the tree. The area of each leaf on the tree corresponds to the amount of information that is stored there.

The great advantage of the treemap over conventional tree views is that the amount of information on each branch of the tree can be easily visualized. Because the method is space-filling, it can show quite large trees containing thousands of branches. The disadvantage is that the non-leaf nodes are not shown and the hierarchical structure is not as clear as it is in a more conventional tree drawing. Of course, there are many hybrid designs where, for example, a node–link representation is used and the size of the node points represents some quantity.

[G6.28] Consider using a treemap to display tree structured data where it is only necessary to display the leaf nodes and where it is important to display a quantity associated with each leaf node.

[G6.29] Consider using a node–link representation of a tree where the hierarchical structure is important, where internal (non-leaf) nodes are important, and where quantitative attributes of nodes are less important.

Patterns in Motion

To this point, we have mainly discussed the use of static patterns to represent data, even though the data is sometimes dynamic—as in the case of a vector field representing a pattern of moving liquid or gas. We can also use motion as a display technique to represent data that is either static or dynamic. The perception of dynamic patterns is not understood as well as the perception of static patterns, but we are very sensitive to

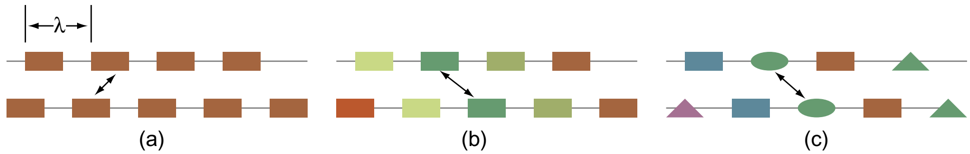


Figure 6.60 (a) If motion is represented using a regular sequence of identical and equally spaced elements, there is a strict limit on the throughput that can be perceived. (b, c) This limit can be extended by varying the sizes and shapes of the graphical elements.

patterns in motion, and if we can learn to use motion effectively it may be a good way to display certain aspects of data.

We start by considering the problem of how to represent data communications with computer animation. One way of doing this is to use a graphical object to represent each packet of information and then to animate that object from the information source to its destination. In the simplest case, data is represented by a series of identical and equally spaced graphical elements, as shown in Figure 6.60. Because the elements are identical, there is a fundamental limitation on the throughput that can be represented. In a computer animation sequence, the basic process is a loop that involves drawing the animated object, displaying it, moving it, and then redrawing it. When this cycle is repeated fast enough, a sequence of static pictures is seen as a smoothly moving image. The limitation on perceived data throughput arises from the amount that a given object can be moved before it becomes confused with another object in the next frame—this is called the *correspondence problem*.

If we define the distance between pattern elements as λ, we are limited to a maximum displacement of $\lambda/2$ on each frame of animation before the pattern is more likely to be seen as moving in the reverse direction from that intended. The problem is illustrated in Figure 6.60(a).

When all the elements are identical, the brain constructs correspondences based on object proximity in successive frames. This is sometimes called the *wagon-wheel effect*, because of the tendency of wagon wheels in Western movies to appear to be rotating in the wrong direction. Experiments by Fleet (1998) suggest that the maximum change per frame of animation for motion to be seen reliably in a particular direction is about $\lambda/3$ for the basic representation shown in Figure 6.60(a). Given an animation frame rate of 60 frames per second, this establishes an upper bound of 20 messages per second that can be represented.

There are many ways in which the correspondence limitation can be overcome by giving the graphical elements a different shape, orientation, or color. Two possibilities are illustrated in Figure 6.60(b) and (c). In one, the gray values of the elements are varied from message to message; in the other, the shapes of the elements are varied. Research with element shapes suggests that correspondence of shape is more important than correspondence of color in determining perceived motion (Caelli et al., 1993). In a series of experiments that examined a variety of enhanced representations like those illustrated in Figure 6.60(b) and (c), Fleet (1998) found that the average phase shift per animation frame could be increased to 3λ before correspondence was lost. Given an animation frame rate of 60 frames per second, this translates to an upper bound of 180 messages per second that can be represented using animation.

Of course, when the goal is to visualize high traffic rates, there is no point in representing individual messages in detail. Most digital communications systems transfer millions of data packets per second. What is important at high data rates is an impression of data volumes, the direction of traffic flow, and large-scale patterns of activity.

Form and Contour in Motion

A number of studies have shown that people can see *relative* motion with great sensitivity. For example, contours and region boundaries can be perceived with precision in fields of random dots if defined by differential motion alone (Regan, 1989; Regan & Hamstra, 1991). Human sensitivity to such motion patterns rivals our sensitivity to static patterns; this suggests that motion is an underutilized method for displaying patterns in data. For purposes of data display, we can treat motion as an attribute of a visual object, much as we consider size, color, and position to be object attributes. We evaluated the use of simple sinusoidal motion in enabling people to perceive correlations between variables (Limoges et al., 1989). We enhanced a conventional scatterplot representation by allowing the points to oscillate sinusoidally, either horizontally or vertically (or both), about a center point. An experiment was conducted to discover whether the frequency, phase, or amplitude of point motion was the most easily "read." The task was to distinguish a high correlation between variables from a low one. A comparison was made with more conventional graphical techniques, including using point size, gray value, and x,y position in a conventional scatterplot. The results showed that data mapped to phase was perceived best; in fact, it was as effective as most of the more conventional techniques, such as the use of point size or gray value. In informal studies, we also showed that motion appears to be effective in revealing clusters of distinct data points in a multidimensional data space (see Figure 6.61). Related data shows up as clouds of points moving together in elliptical paths, and these can be easily differentiated from other clouds of points.

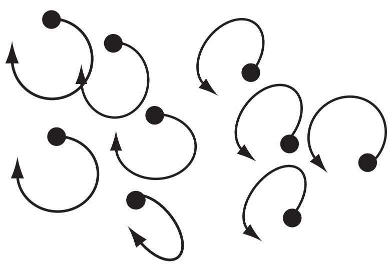


Figure 6.61 An illustration of the elliptical motion paths that result when variables are mapped to the relative phase angles of oscillating dots. The result is similar elliptical motion paths for points that are similar. In this example, two distinct groups of oscillating dots are clearly perceived.

Moving Frames

Perceived motion is highly dependent on its context. A rectangular frame provides a very strong contextual cue for motion perception, as shown in Figure 6.62(a). It is so strong that if a bright frame is made to move around a bright static dot in an otherwise completely dark environment, it is often the static dot that appears to move (Wallach, 1959). Johansson (1975) has demonstrated a number of grouping phenomena that show that the brain has a strong tendency to group moving objects in a hierarchical fashion. One of the effects he investigated is illustrated in Figure 6.62(b) and (c). In this example, three dots are set in motion. The two outer dots move in synchrony in a horizontal direction. The third dot, located between the other two, also moves in synchrony but in an oblique direction; however, the central dot is not perceived as moving along an oblique path as shown in Figure 6.62(b). Instead, what is perceived is illustrated in Figure 6.62(c). An overall horizontal motion of the entire group of dots is seen; within this group, the central dot also appears to move vertically.

Computer animation is often used in a straightforward way to display dynamic phenomena, such as a particle flow through a vector field. In these applications, the main goal from a perceptual point of view is to bring the motion into the range of human sensitivities. The issue is the same for viewing high-speed or single-frame movie photography. The motions of flowers blooming or bullets passing through objects are speeded up and slowed down, respectively, so that we can perceive the dynamics of the phenomena. Humans are most sensitive to motion ranging from 0.5 cm to 4 cm per second for objects viewed at normal screen distances (Dzhafarov et al., 1993).

> **[G6.30]** When animation is used in a visualization, aim for motion in the range of 0.5 to 4 degrees/second of visual angle.

The use of motion to help us distinguish patterns in abstract data is at present only a research topic, albeit a very promising one. One application of the research results is the use of frames to examine dynamic flow-field animations. Frames can be used as an effective device for highlighting local relative motion. If we wish to highlight the

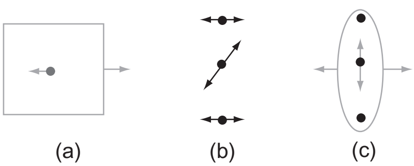


Figure 6.62 (a) When a stationary dot is placed within a moving frame in a dark room, it is the dot that is perceived to move in the absence of other cues. (b) When dots are set in synchronized motion, they form a frame within which individual motion is seen. (c) The entire group of dots is seen to move horizontally, and the central dot moves vertically within the group.

local relative motion of a group of particles moving through a fluid, a rectangular frame that moves along with the group will create a reference area within which local motion patterns can emerge.

Another way in which motion patterns are important is in helping us perceive visual space and rigid three-dimensional shapes. This topic is covered in Chapter 8 in the context of the other mechanisms of space perception.

Expressive Motion

Using moving patterns to represent motion on communication channels, or in vector fields, is a rather obvious use of motion for information display, but there are other, more subtle uses. There appears to be a vocabulary of expressive motion comparable in richness and variety to the vocabulary of static patterns explored by the Gestalt psychologists. In the following sections, some of the more provocative results are discussed, together with their implications for data visualization.

Perception of Causality

When we see a billiard ball strike another and set the second ball in motion, we perceive that the motion of the first ball *causes* the motion of the second, according to the work of Michotte (translated 1963). Michotte's book, *The Perception of Causality*, is a compendium of dozens of experiments, each showing how variations in the basic parameters of velocity and event timing can radically alter what is perceived. He conducted detailed studies of the perception of interactions between two patches of light and came to the conclusion that the perception of causality can be as direct and immediate as the perception of simple form. In a typical experiment, illustrated in Figure 6.63, one rectangular patch of light moved from left to right until it just touched a second patch of light and then stopped. At this point, the second patch of light would start to move. This was before the advent of computer graphics, and Michotte conducted his experiments with an apparatus that used little mirrors and beams of light. Depending on the temporal relationships between the moving light events and their relative velocities, observers reported different kinds of causal relationships, variously described as "launching," "entraining," or "triggering."

Precise timing is required to achieve perceived causality. Michotte found that, for the effect he called *launching* to be perceived, the second object had to move within

Figure 6.63 Michotte (1963) studied the perception of causal relationships between two patches of light that always moved along the same line but with a variety of velocity patterns.

70 milliseconds of contact; after this interval, subjects still perceived the first object as setting the second object in motion, but the phenomenon was qualitatively different. He called it *delayed launching*. Beyond about 160 milliseconds, there was no longer an impression that one event caused the other; instead, the movements of the two objects were perceived as separate. Figure 6.64 shows some of his results. For causality to be perceived, visual events must be synchronized within at least one-sixth of a second. Given that virtual-reality animation often occurs at only about 10 frames per second, events should be frame accurate for clear causality to be perceived.

If an object makes contact with another and the second object moves off at a much greater velocity, a phenomenon that Michotte called *triggering* is perceived. The first object does not seem to cause the second object to move by imparting its own energy; rather, it appears that contact triggers *propelled* motion in the second object.

More recent developmental work by Leslie and Keeble (1987) has shown that infants at only 27 weeks of age can perceive causal relations such as launching. This would appear to support the contention that such percepts are in some sense basic to perception.

The significance of Michotte's work for data visualization is that it provides a way to increase the expressive range beyond what is possible with static diagrams. In a static visualization, the visual vocabulary for representing relationships is quite limited. To show that one visual object is related to another, we can draw lines between them, we can color or texture groups of objects, or we can use some kind of simple shape coding. The only way to show a causal link between two objects is by using some kind of conventional code, such as a labeled arrow; however, such codes owe their meaning more to our ability to understand conventional coded language symbols than to anything essentially perceptual. Arrows are used to show many kinds of directed relationships, not just causal ones. This point about the differences between language-based

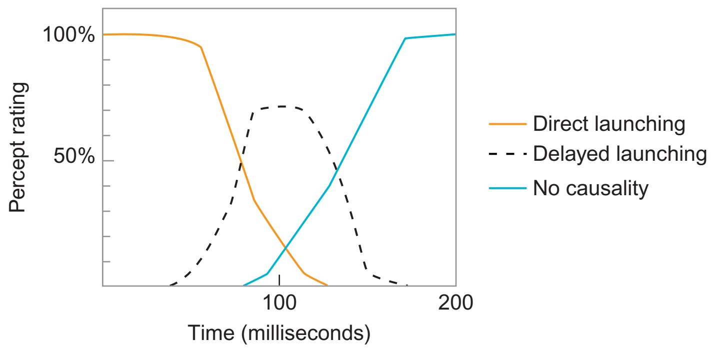


Figure 6.64 When one object comes into contact with another and the second moves off, the first motion may be seen to cause the second if the right temporal relationships exist. The graph shows how different kinds of phenomena are perceived, depending on the delay between the arrival of one object and the departure of the other. (*From* Michotte (1963)*. Reproduced with permission*.)

codes and perceptual codes is elaborated in Chapter 9. What Michotte's work gives us is the ability to significantly enrich the vocabulary of things that can be immediately and directly represented in a diagram, although it would be premature to recommend this as a specific guideline.

Perception of Animated Motion

In addition to the fact that we can perceive causality using simple animation, there is evidence that we are highly sensitive to motion that has a biological origin. In a series of now classic studies, Gunnar Johansson attached lights to the limb joints of actors (Johansson, 1973). He then produced moving pictures of the actors carrying out certain activities, such as walking and dancing. These pictures were made so that only the points of light were visible, and, in any given still frame, all that was perceived was a rather random-seeming collection of dots, as shown in Figure 6.65(a). But, once the dots were animated, viewers were immediately conscious of the fact that they were watching human motion. In addition, they could identify the genders of the actors and the tasks they were performing. Some of these identifications could be made after exposures lasting only a small fraction of a second.

Another experiment pointing to our ability to recognize form from motion was a study by Heider and Simmel (1944). In this study, an animated movie was produced incorporating the motion of two triangles and a circle, as shown in Figure 6.65(b). People viewing this movie readily attributed human characteristics to the shapes; they would say, for example, that a particular shape was angry or that the shapes were chasing one another. Moreover, these interpretations were consistent across observers. Because the figures were simple shapes, the implication is that patterns of motion were conveying the meaning. Other studies support this interpretation. Rimé et al. (1985) did a cross-cultural evaluation of simple animations using European, American, and African subjects and found that motion could express such concepts as kindness, fear, and

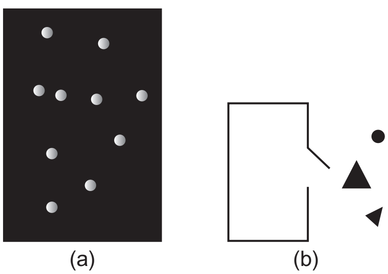


Figure 6.65 (a) In Johansson's (1973) experiments, a pattern of moving dots was produced by making a movie of actors with lights attached to parts of their bodies. (b) Heider and Simmel (1944) made a movie of simple geometric shapes moving through complex paths. Viewers of both kinds of displays attribute anthropomorphic characteristics to what they see.

aggression. There was considerable similarity in these interpretations across cultures, suggesting some measure of universality.

Enriching Diagrams with Simple Animation

The research findings of Michotte, Johansson, Heider, Semmel, and others suggest that the use of simple motion can powerfully express certain kinds of relationships in data. Animation of abstract shapes can significantly extend the vocabulary of things that can be conveyed naturally beyond what is possible with a static diagram. The fact that motion does not require the support of complex depictive representations (of animals or people) for movement to be perceived as animate means that simplified motion techniques may be useful in multimedia presentations. The kinds of animated critters that are starting to crawl and hop over web pages are often unnecessary and distracting. Just as elegance is a virtue in static diagrams, so is it a virtue in diagrams that use animation. A vocabulary of simple expressive animation requires development, but research results strongly suggest that this will be a productive and worthwhile endeavor. The issue is pressing, because animation tools are becoming more widely available for information display systems. More design work and more research are needed.

The Processes of Pattern Finding

We conclude this chapter with some remarks on the process within which the pattern-finding machinery of the brain operates. When we look at something that is well known to us, what we perceive is largely a product of information stored in our brains. For the most part we see what we know, but the discovery of novel patterns is very different, since the brain does not have the same memory resources to build meaning.

In data exploration, cognitive task demands lead to the formation of visual queries, and this results in a retuning of the different channels. If the task seems to require information stored in color channels, then that information will be neurally enhanced, and colored targets will become more distinct. In this respect, looking for patterns is the same as looking for individual glyphs, as discussed in the previous chapter.

Ullman (1984) proposed that low-level processes run in the brain to pull out abstract patterns, and, in this chapter, we have seen research suggesting how these may operate in terms of extended contours, and suggested that similar mechanisms exist for regions of common texture or color. A key point about Ullman's theory is that only a small number of pattern operators can run simultaneously. We can only mentally trace a very small number of contours, probably fewer than five at the same time, if they are simple and only one that is slightly more complex. The same goes for regions defined by texture or color. The theory of *attentional shrouds* proposes that there are mechanisms whereby regions of different texture compete for attention (Bhatt et al., 2007). How attention is

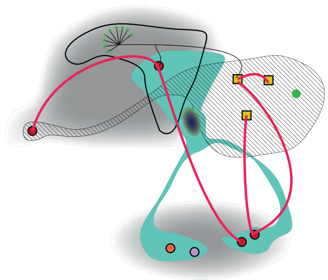


Figure 6.66 Try this subjective experiment. Attend to different components and notice how the other parts fade from consciousness.

allocated to them depends both on how salient they are and the top-down influence of visual queries derived from the cognitive task of the moment.

Figure 6.66 is designed to support a phenomenological self-experiment. It deliberately uses different channels in showing a variety of interrelated structures. To appreciate it, make visual queries such as "Are all the yellow squares connected by the red lines?" or "What kinds of symbols lie on the blue region?" Notice how, as you look at the display to answer these questions, certain features become more visually distinct and others fade. This is due to both eye movements and the action of attention acting through the medium of the visual channels, pulling out certain pattern components. In later chapters, we will delve deeper into the processes of visual thinking, but for now it is important to note that there are strict limits on the complexity of a novel pattern that can be held in the mind. Beyond a certain complexity, novel patterns cannot be easily grasped.

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CHAPTER SEVEN

Space Perception

We live in a three-dimensional world (actually, four dimensions if time is included). In the short history of visualization research, most graphical display methods have required that data be plotted on sheets of paper, but computers have evolved to the point that this is no longer necessary. Now we can create the illusion of three-dimensional (3D) space behind the monitor screen, changing over time if we wish. The big question is why should we do this? There are clear advantages to conventional two-dimensional (2D) techniques, such as the bar chart and the scatterplot. The most powerful pattern-finding mechanisms of the brain work in 2D, not 3D. Designers already know how to draw diagrams and represent data effectively in two dimensions, and the results can easily be included in books and reports. Of course, one compelling reason for an interest in 3D space perception is the explosive advance in 3D computer graphics. Because it is so inexpensive to display data in an interactive 3D virtual space, people are doing it—often for the wrong reasons. It is inevitable that there is now an abundance of ill-conceived 3D design, just as the advent of desktop publishing brought poor use of typography and the advent of cheap color brought ineffective and often garish use of color. Through an understanding of space perception, we hope to reduce the amount of poor 3D design and clarify those instances in which 3D representation is really useful.

The first half of this chapter presents an overview of the different factors, called *depth cues*, involved in the perception of 3D space. This will provide the foundation for the second half, which is about how these cues can be effectively applied in design. The way we use spatial information depends greatly on the task at hand. Docking one

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object with another or trying to trace a path in a tangled web of imaged blood vessels require different ways of seeing. The second half gives a task-based analysis of the ways in which different cues are used in performing seven different tasks, ranging from tracing paths in 3D networks to judging the morphology of surfaces to appreciating an aesthetic impression of spaciousness.

Depth Cue Theory

The visual world provides many different sources of information about 3D space. These sources are usually called *depth cues*, and a large body of research is related to the way the visual system processes depth cue information to provide an accurate perception of space. Following is a list of the more important depth cues. They are divided into categories according to whether they can be reproduced in a static picture (monocular static) or a moving picture (monocular dynamic) or require two eyes (binocular).

Monocular static (pictorial)

- Linear perspective
- Texture gradient
- Size gradient
- Occlusion
- Depth of focus
- Shape-from-shading
- Vertical position
- Relative size to familiar objects
- Cast shadows
- Depth-from-eye accommodation (this is nonpictorial)

Monocular dynamic (moving picture)

- Structure-from-motion (kinetic depth, motion parallax)

Binocular

- Eye convergence
- Stereoscopic depth

More attention is devoted to stereoscopic depth perception than to the other depth cues, not because it is the most important—it is not—but because it is relatively complex and because it is difficult to use effectively.

Perspective Cues

Figure 7.1 shows how perspective geometry can be described for a particular viewpoint and a picture plane. The position of each feature on the picture plane is determined by extending a ray from the viewpoint to that feature in the environment. If the resulting picture is subsequently scaled up or down, the correct viewpoint is specified by similar triangles, as shown. If the eye is placed at the specified point with respect to the picture, the result is a correct perspective view of the scene. A number of the depth cues are direct results of the geometry of perspective. These are illustrated in Figures 7.2 and 7.3.

- Parallel lines converge to a point.
- Objects at a distance appear smaller on the picture plane than do nearby objects. Objects of known size may have a very powerful role in determining the perceived size of adjacent unknown objects. An image of a person placed in a picture of otherwise abstract objects gives a scale to the entire scene.
- Uniformly textured surfaces result in texture gradients in which the texture elements become smaller with distance.

In terms of the total amount of information available from an information display, there is no evidence that a perspective picture lets us see *more* than a non-perspective image. A study by Cockburn and McKenzie (2001) showed that perspective cues added no advantage to a version of the Data Mountain display of Robertson et al. (1998). The version shown in Figure 7.4(b) was just as effective as the one in Figure 7.4(a); however,

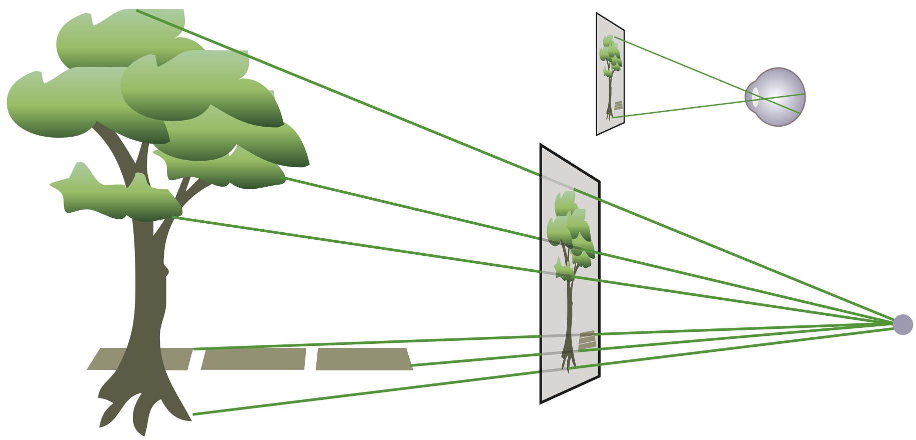


Figure 7.1 The geometry of linear perspective is obtained by sending a ray from each point in the environment through a picture window to a single fixed point. To obtain a perfect perspective picture, each point on the picture window is colored according to the light that emanates from the corresponding region of the environment. The result is that objects vary in size on the picture plane in inverse proportion to their distance from the fixed point. If an image is created according to this principle, the correct viewpoint is determined by similar triangles, as shown in the upper right.

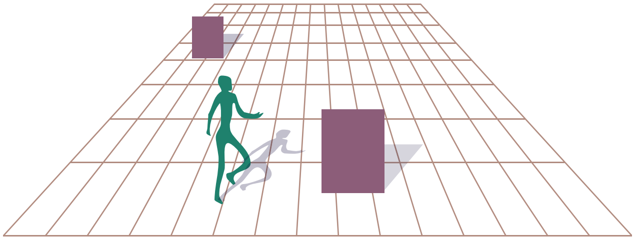


Figure 7.2 Perspective cues arising from perspective geometry include the convergence of lines and the fact that more distant objects become smaller on the picture plane.

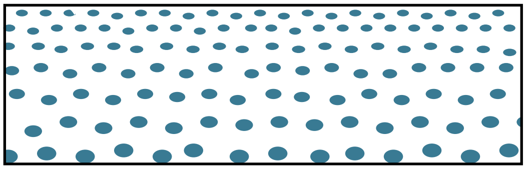


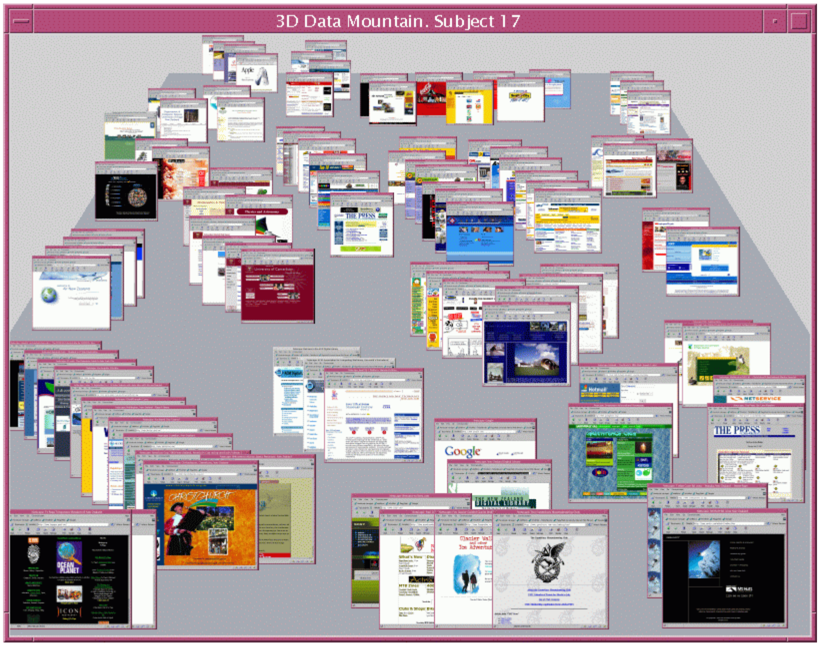
Figure 7.3 A texture gradient is produced when a uniformly textured surface is projected onto the picture plane.

both of these versions make extensive use of other depth cues, occlusion, and height on the picture plane.

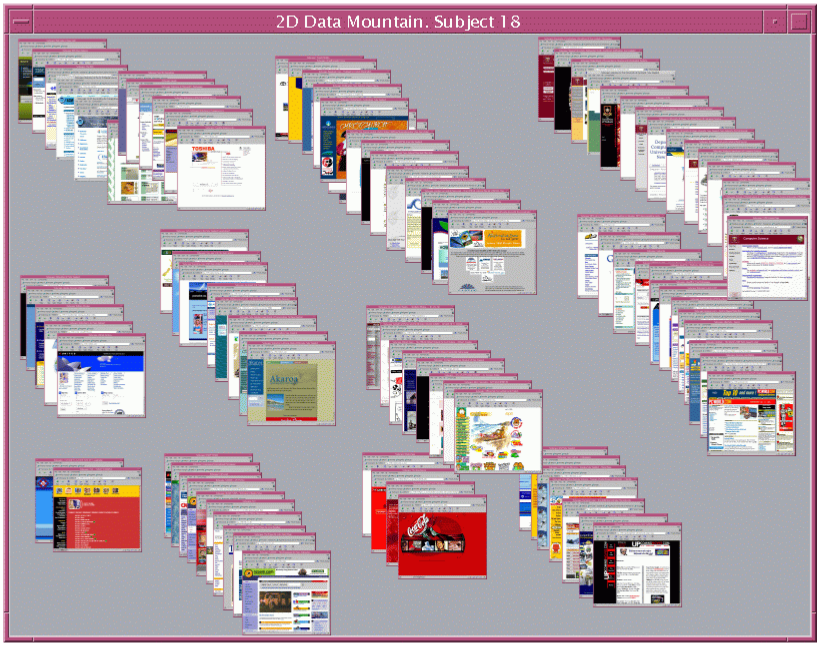
The Duality of Depth Perception in Pictures

In the real world, we generally perceive the actual size of an object rather than the size at which it appears on a picture plane (or on the retina). This phenomenon is called *size constancy*. The degree to which size constancy is obtained is a useful measure of the relative effectiveness of depth cues. When we perceive pictures of objects, we enter a kind of dual perception mode. To some extent, we have a choice between accurately judging the size of a depicted object as though it exists in a 3D space and accurately judging its size on the picture plane (Hagen, 1974). The amount and effectiveness of the depth cues used will, to some extent, make it easy to see in one mode or the other. The picture plane sizes of objects in a very sketchy schematic picture are easy to perceive. At the other extreme, when viewing a highly realistic stereoscopic moving picture at a movie theater, the 3D sizes of objects will be more readily perceived, but in this case large errors will be made in estimating picture plane sizes. Figure 7.5 shows how perspective cues can affect the perceived size of two objects that have identical sizes on the picture plane. This has implications if accurate size judgments are required in a visualization.

> **[G7.1]** If accurate size judgments are required for abstract 3D shapes viewed in a computer-generated 3D scene, provide the best possible set of depth cues.



(a)



(b)

Figure 7.4 (a) Variation on the Robertson et al. (1998) Data Mountain display. (*Courtesy of Andy Cockburn*.) (b) Same as (a) but without perspective.

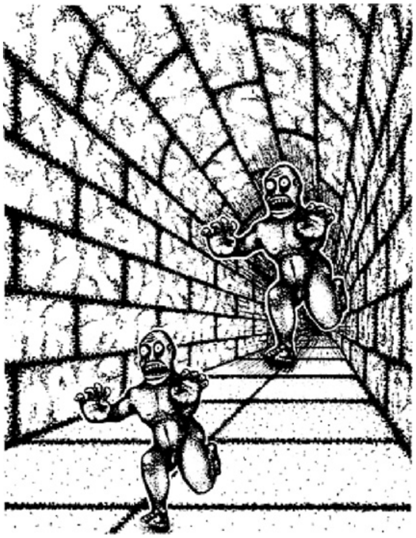


Figure 7.5 Because of the strong perspective cues the figure above looks much bigger than the one below, even though they are the same size. This would be even more pronounced with greater realism and stereoscopic cues. In the image plane the two figures are identical. (*From http://www.sapdesignguild.org/contact.asp. (With permission).*)

Pictures Seen from the Wrong Viewpoint

It is obvious that most pictures are not viewed from their correct centers of perspective. In a movie theater, only one person can occupy this optimal viewpoint (determined by viewpoint position, the focal length of the original camera, and the scale of the final picture). When a picture is viewed from somewhere other than the center of perspective, the laws of geometry suggest that significant distortions should occur. Figure 7.6 illustrates this. When the mesh shown in Figure 7.6 is projected on a screen with a geometry based on viewpoint (a), but actually viewed from position (b), it should be perceived to stretch along the line of sight as shown. However, although people report seeing some distortion at the start of looking at moving pictures from the wrong viewpoint, they become unaware of the distortion after a few minutes. Kubovy (1986) calls this the *robustness of linear perspective*. Apparently, the human visual system overrides some aspects of perspective in constructing the 3D world that we perceive.

One of the mechanisms that can account for this lack of perceived distortion may be a built-in perceptual assumption that objects in the world are rigid. Suppose that the mesh in Figure 7.6 is smoothly rotated around a vertical axis and projected assuming the correct viewpoint, but viewed from an incorrect viewpoint. It should appear as a nonrigid, elastic body, but perceptual processing is constrained by a rigidity assumption, and this causes us to see a stable, nonelastic 3D object.

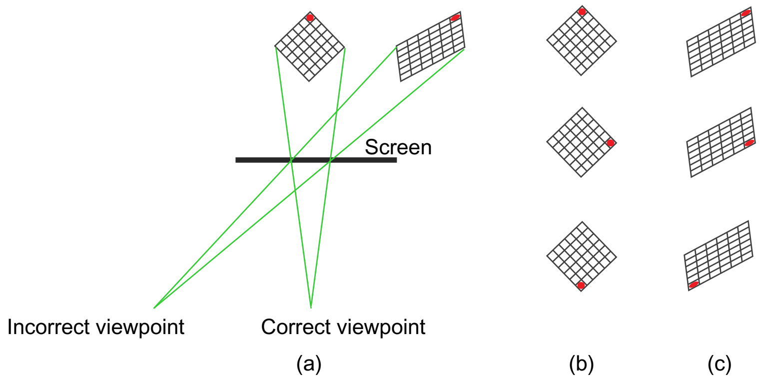


Figure 7.6 (a) When a perspective picture is seen from the wrong viewpoint, simple geometry predicts that large distortions should be seen. In fact, they are not seen or, when seen, are minimal. (b) A rotating object seen from the incorrect viewpoint appears undistorted. (c) Were the mental calculation based on simple geometry, it should appear to warp as shown in the top-to-bottom sequence.

Under extreme conditions, some distortion is still seen with off-axis viewing of moving pictures. Hagen and Elliott (1976) showed that this residual distortion is reduced if the projective geometry is made more parallel. This can be done by simulating long-focal-length lenses, which may be a useful technique if displays are intended for off-axis viewing.

> **[G7.2]** To minimize perceived distortions from off-axis viewing of 3D data spaces, avoid extremely wide viewing angles when defining perspective views. As a rule of thumb, keep the horizontal viewing angle below 30 degrees.

Various technologies exist that can track a user's head position with respect to a computer screen and thereby estimate the position of the eye(s). With this information, a 3D scene can be computed and viewed so the perspective is "correct" at all times by adjusting the viewpoint parameters in the computer graphics software (Deering, 1992). I called this setup *fish-tank virtual reality* to contrast it with the immersive virtual reality that is obtained with head-mounted displays (Ware et al., 1993). It is like having a small, bounded, fish-tank-sized artificial environment with which to work. There are two reasons why this might be desirable, despite the fact that incorrect perspective viewing of a picture seems generally unimportant. The first reason is that, as an observer changes position, the perspective image will change accordingly, resulting in motion parallax. Motion parallax is itself a depth cue, as discussed later in the structure-from-motion section. The second reason is that in some virtual-reality systems it is possible to place the subject's hand in the same space as the virtual computer graphics imagery. Figure 7.7 shows an

Figure 7.7 A user is attempting to trace 3D blood vessels in an interface that puts his hands in the same space as the virtual computer graphics imagery. (*From Serra et al. (1997). Reproduced with permission.*)

apparatus that uses a half-silvered mirror to combine computer graphics imagery with a view of the user's own hand. To get the registration between the hand and virtual objects correct, the eye position must be tracked and the perspective computed accordingly.

When virtual-reality head-mounted displays are used, it is essential that the perspective be coupled to a user's head movement, because the whole point is to allow users to change viewpoint in a natural way. Experimental evidence supports the idea that head-coupled perspective enhances the sense of presence in virtual spaces more than stereoscopic viewing (Arthur et al., 1993; Pausch et al., 1996).

Occlusion

If one object overlaps or occludes another, it appears closer to the observer (see Figure 7.8). This is probably the strongest depth cue, overriding all the others, but it provides only binary information. An object is either behind or in front of another; no information is given about the distance between them. A kind of partial occlusion occurs when one object is transparent or translucent. In this case, there is a color difference between the parts of an object that lie behind the transparent plane and the parts that are in front of it.

Occlusion can be useful in design; for example, the tabbed cards illustrated in Figure 7.9(a) use occlusion to provide rank-order information, in addition to rapid access to individual cards. Although modern graphical user interfaces (GUIs) are

Figure 7.8 The figures depicted on the left can be seen as having the same size but different distances. On the right, the occlusion depth cue ensures that we see the upper figure as at the same depth or closer than the left figure. It therefore appears smaller.

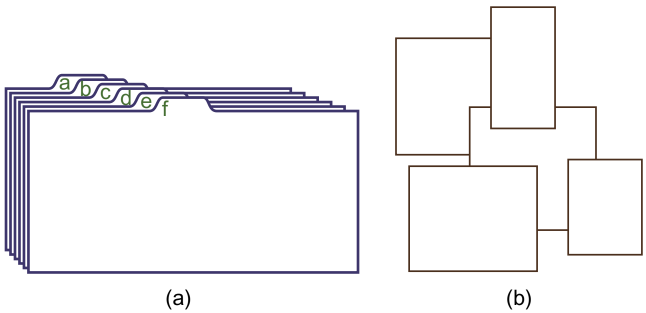


Figure 7.9 (a) Careful use of occlusion enables small tabs to provide access to larger objects. (b) Window interfaces use occlusion.

usually described as being 2D, they are actually 3D in a nontrivial way. Overlapping windows rely on our understanding of occlusion to be effective; see Figure 7.9(b).

Shape-from-Shading

Continuous surfaces are common in 3D visualization, and the shape of their bumps, ridges, and indentations can contain important information. Examples include digital elevation maps representing the topography of the land or the ocean floor; maps of physical properties of the environment, such as pressure and temperature; and maps representing mathematical functions that are only distantly related to the raw data. These kinds of data objects are variously called *2D scalar fields*, *univariate maps*, or *2D manifolds*. The two traditional methods for displaying scalar field information are the contour map, which originated in cartography, and the pseudocolor map, discussed in Chapter 4. Here we consider using the spatial cues that let us perceive curved surfaces in the world, mainly shape-from-shading and conformal texture.

Shading Models

The basic shading model used in computer graphics to represent the interaction of light with surfaces has already been discussed in Chapter 2. It has four basic components, as follows:

1. **Lambertian shading**—Light reflected from a surface equally in all directions
2. **Specular shading**—Highlights reflected from a glossy surface
3. **Ambient shading**—Light coming from the surrounding environment
4. **Cast shadows**—Shadows cast by an object, either on itself or on other objects

Figure 7.10 illustrates the shading model, complete with cast shadows, applied to a digital elevation map of San Francisco Bay. As can be seen, even this simple lighting model is capable of producing a dramatic image of surface topography. A key question in choosing a shading model for data visualization is not its degree of realism

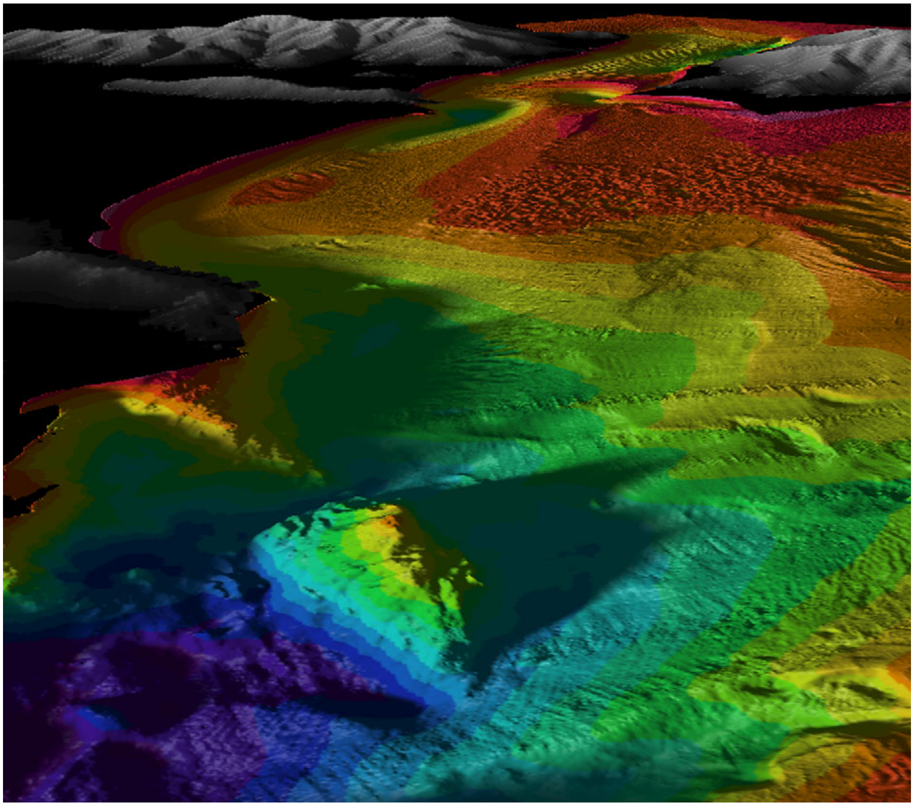


Figure 7.10 A shaded representation of the floor of San Francisco Bay, shown as if the water had been drained out of it. (*Data courtesy of James Gardner, U.S. Geological Survey. Image constructed using IVS Fledermaus software.*)

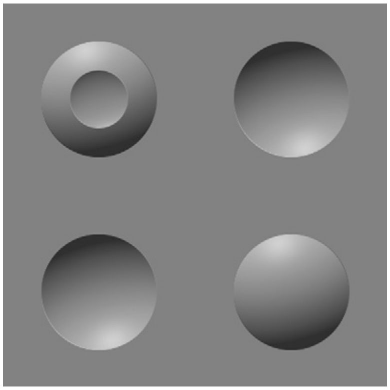


Figure 7.11 The brain generally assumes that lighting comes from above. The bumps in this image become hollows when the picture is turned upside down, and *vice versa*.

but how well it reveals the surface shape. There is some evidence that more sophisticated lighting may actually be harmful in representing surfaces.

Experiments by Ramachandran (1988) suggest that the brain assumes a single light source from above in determining whether a particular shaded area is a bump or a hollow (see Figure 7.11). The kinds of complex shadows that result from multiple light sources and radiosity modeling may be visually confusing rather than helpful. As discussed in Chapter 2 (Figure 2.8) specular highlights can be extremely useful in revealing fine surface details, as when a light is used to show scratches on glass. At other times, highlights will obscure patterns of surface color.

A clever use of shape-from-shading is shown in Figure 7.12. van Wijk and Telea (2001) developed a method that allows for the perception of surface shape using shape-from-shading information. In addition, they added ridges that also allow for contours to be perceived.

Shading information can also be useful in emphasizing the affordances of display widgets such as buttons and sliders, even in displays that are very flat. Figure 7.13 illustrates a slider enhanced with shading. This technique is widely used in today's graphical user interfaces.

Cushion Maps

The treemap visualization technique was introduced in Chapter 6 and illustrated in Figure 6.59 (Johnson & Shneiderman, 1991). As discussed, a problem with treemaps is that they do not convey tree structure well, although they are extremely good at showing the sizes and groupings of the leaf nodes. An interesting solution devised by van Wijk and van de Wetering (1999) makes use of shading. They called it a *cushion map*. To create it, the hierarchical shading model is applied to a treemap in such a way that areas representing large branches are given an overall shading, and regions

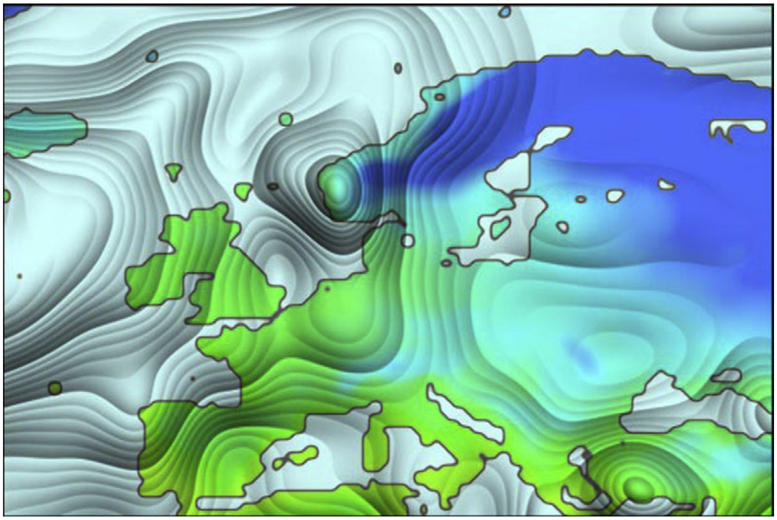


Figure 7.12 In this image, the average precipitation over Europe for January has been converted to a smoothed surface using the method of van Wijk and Telea (2001). The shape of this surface is revealed through shape-from-shading information.

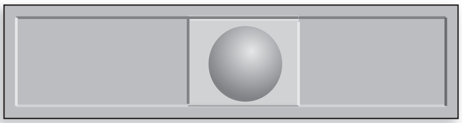


Figure 7.13 Even with mostly 2D interfaces, subtle shading can make sliders and other widgets look like objects that can be manipulated.

representing smaller branches are given their own shading within the overall shading. This is repeated down to the leaf nodes, which have the smallest scale shading. An example is shown in Figure 7.27 showing a computer file system. As can be seen, the hierarchical structure of the system is more visible than it would be in an unshaded treemap.

Surface Texture

Surfaces in nature are generally textured. Gibson (1986) took the position that surface texture is an essential property of a surface. A nontextured surface, he said, is merely a patch of light. The way in which textures wrap around surfaces can provide valuable information about surface shape.

Without texture, it is usually impossible to distinguish one transparent curved surface from another transparent curved surface lying beneath it. Figure 7.15 shows an illustration

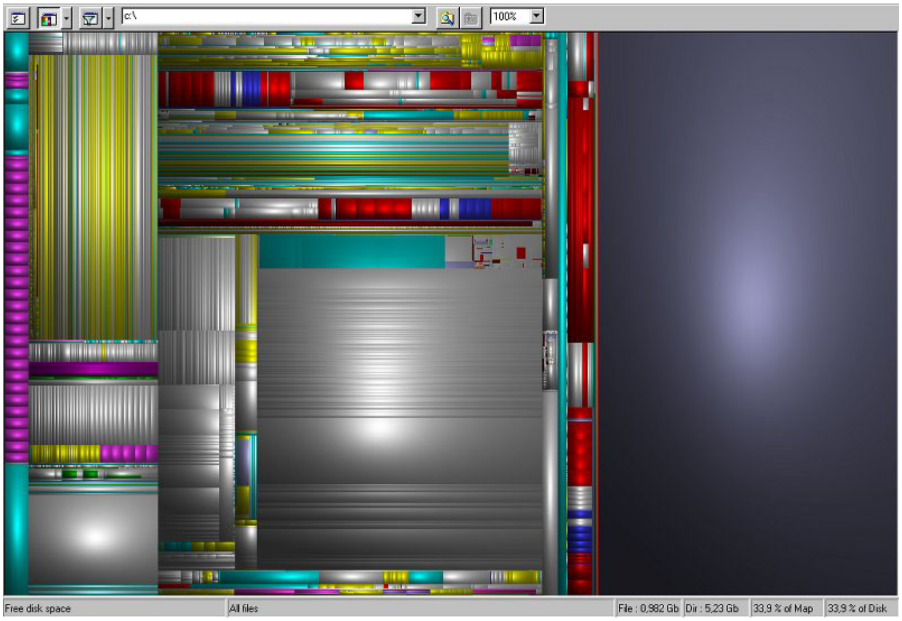


Figure 7.14 The cushion map is a variation of a treemap that uses shape-from-shading information to reveal hierarchical structure. (*Courtesy of Jack van Wijke.*)

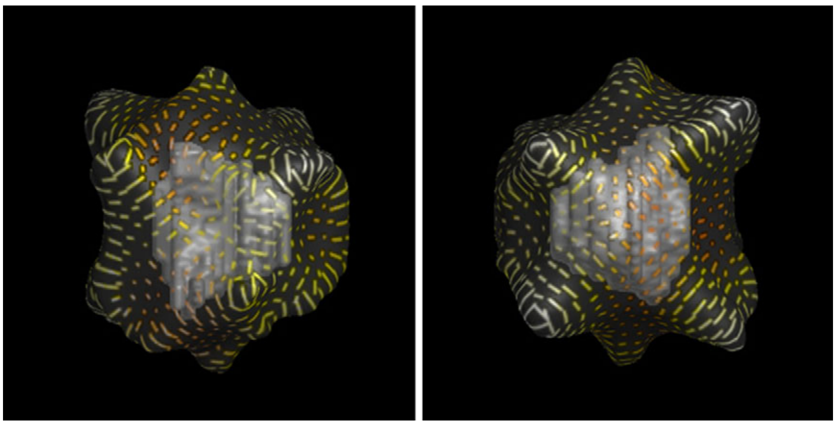


Figure 7.15 Textures designed to reveal surface shape so another surface can be seen beneath. (*From Interrante et al. (1997). Reproduced with permission.*)

from Interrante et al. (1997) containing experimental see-through textures designed to reveal one curved surface lying above another. The concept of laciness, discussed in Chapter 6, is relevant here, because it tells us something about how to make layers visually distinct and thereby clearly show separate surfaces, one beneath another.

There are many ways to make oriented textures conform to a surface. Texture lines can be constructed to follow the fall line (down slope), to be horizontal contours, to be at right angles to maximum curvature direction, or to be orthogonal to the line of site of a viewer, to present just a few examples.

Kim et al. (2003) investigated combinations of first and second principal directions of curvature contours, as illustrated in Figure 7.16 (the principal curvature direction is the direction of maximum curvature). All of the textured surfaces were artificially lit using standard computer graphics shading algorithms. Subjects made smaller errors in surface orientation judgments when two contour directions were used to form a mesh, as shown in Figure 7.16(a). Nevertheless, this study and Norman et al. (1995) found that errors *averaged* 20 degrees. This is surprisingly large and suggests that further gains are possible.

A simpler way of a revealing the shape of a surface through texture is to drape a regular grid mesh over it (Sweet & Ware, 2004; Bair et al. 2009). See Figure 7.17. More studies

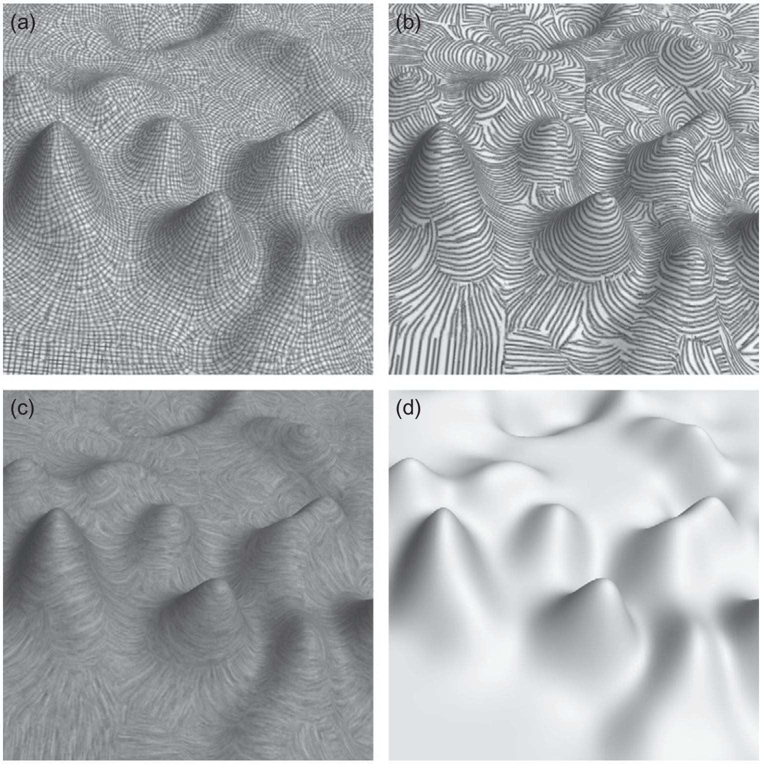


Figure 7.16 Surface-revealing texture patterns. (a) Two-directional texture pattern following first and second principal directions. (b) One-directional texture pattern following first principal curvature direction. (c) One-directional, line-integral convolutions texture following first principal curvature direction. (d) No texture. (*From* Kim et al. (2003). *Reproduced with permission.*)

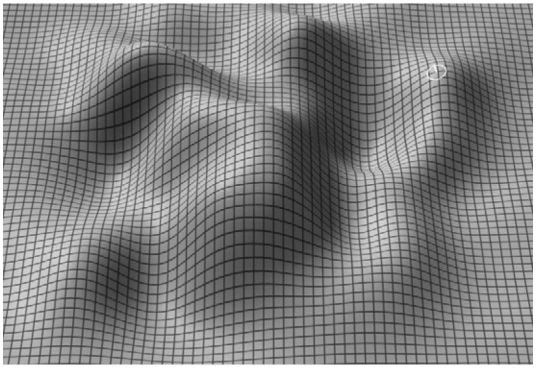


Figure 7.17 Simple draped grids can help reveal surface shape.

are needed to do direct comparisons between the various conformal texture generation methods, but cross-paper comparisons suggest that simple draped meshes yield smaller errors than the fall line or principal curvature textures, as Bair et al. (2009) measured mean errors of less than 12 degrees using grids. In addition, if grids are constructed with a standard cell size they provide useful scale information. Another interesting result is that perspective views result in smaller errors than plan views.

[G7.3] In 3D visualizations of height field data, consider using draped grids to enhance surface shape information. This is likely to be most useful where the data varies smoothly so surface shape features are substantially larger than grid squares.

Cast Shadows

Cast shadows are a very potent cue to the height of an object above a plane, as illustrated in Figure 7.18. They can function as a kind of indirect depth cue—the shadow locates the object with respect to some surface in the environment. In the case of Figure 7.18, this surface is not present in the illustration but is assumed by the brain. In a multi-factor experiment, Wanger et al., (1992) found that shadows provided the strongest depth cue when compared to texture, projection type, frames of reference, and motion. It should be noted, however, that they used an oblique checkerboard as a base plane to provide the actual distance information, so strictly speaking the checkerboard was providing the depth cue. Cast shadows function best as a cue to height above surface when there is a relatively small distance between the object and the surface. They can be especially effective in showing when an object is very close to the point of contact (Madison et al., 2001).

Kersten et al. (1997) showed that cast shadows are especially powerful when objects are in motion. One of their demonstrations is illustrated in Figure 7.19(b). In this case, the

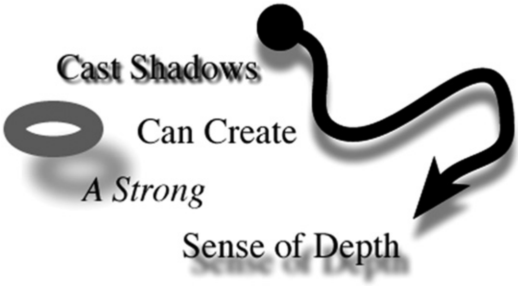


Figure 7.18 Cast shadows can be useful in making data appear to stand above an opaque plane.

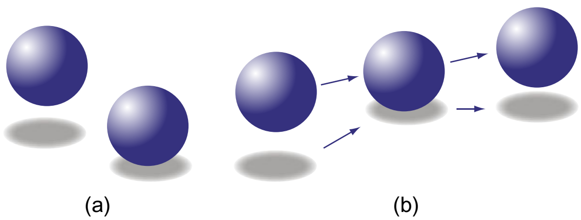


Figure 7.19 (a) Shadows can provide a strong cue for the relative height of objects above a plane. (b) The effect is even stronger with motion. The ball actually appears to bounce when the ball and shadows are animated to follow the trajectories shown by the arrows.

apparent trajectory of a ball moving in 3D space is caused to change dramatically depending on the path of the object's shadow. The image of the ball actually travels in a straight line, but the ball appears to bounce because of the way the shadow moves. In this study, shadow motion was shown to be a stronger depth cue than change in size with perspective.

It has been shown that shadows can be correctly interpreted without being realistic. Kersten et al., (1996) found no effect of shadow quality in their results; however, one of the principal cues in distinguishing shadows from non-shadows in the environment is the lack of sharpness in shadow edges. Fuzzy-edged shadows are likely to lead to less confusing images.

Cast shadows are useful in distinguishing information that is layered a small distance above a planar surface, as illustrated in Figure 7.18. In this case, they are functioning as a depth cue. This technique can be applied to layered map displays of the type used in geographical information systems (GISs).

In complex environments, however, where objects are arranged throughout 3D space, cast shadows can be confusing rather than helpful, because it may not be possible to determine perceptually which object is casting a particular shadow.

> **[G7.4]** In 3D data visualizations, consider using cast shadows to tie objects to a surface that defines depth. The surface should provide strong depth cues, such as a grid texture. Only use cast shadows to aid in depth perception where the surface is simple and where the objects casting the shadow are close to it.

Distance Based on Familiar Size

Many objects that we see have a known size and this can be used to help us judge distance. Figure 7.20 illustrates this. The German shepherd dog and the chair are objects known to be of roughly comparable size; therefore, we see them as at the same distance in the composition on the left. A different interpretation is available on the right, where the size and vertical position depth cues are consistent with the result that the dog is seen as more distant than the chair.

Depth of Focus

When we look around, our eyes change focus to bring the images of fixated objects into sharp focus on the fovea. As a result, the images of both nearby and more distant objects become blurred, making blur an ambiguous depth cue. In an image with some objects that are sharp and others that are blurred, all the sharp objects tend to be seen

Figure 7.20 On the left, we see a picture of a dog and a chair, arranged rather arbitrarily but appearing to be the same distance from the viewer. On the right, the known sizes of dog and chair are consistent with another interpretation, that of a coherent 3D scene with the dog at a greater distance.

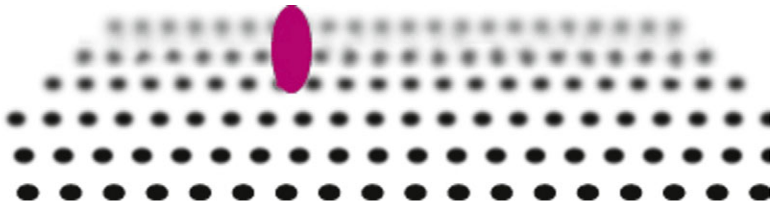


Figure 7.21 The eye adjusts to bring objects of interest into sharp focus. As a result, objects that are closer or more distant become blurred.

at a single distance, and the blurred objects tend to be seen at a different distance, either closer or farther away. Focus effects are important in separating foreground objects from background objects, as shown in Figure 7.21. Perhaps because of its role as a depth cue, simulating depth of focus is an excellent way to highlight information by blurring everything except that which is critical. Of course, this only makes sense if the critical information can be reliably predicted.

The effect of depth of focus can be properly computed only if the object of fixation can be predicted. In normal vision, our attention shifts and our eyes refocus dynamically depending on the distance of the object fixated. Chapter 2 describes a system designed to change focus information based on a measured point of fixation in a virtual environment.

Eye Accommodation

The eye changes focus to bring attended objects into sharp focus on the retina. If the brain could measure the eye's accommodation this might be a depth cue. But, because we are only capable of focusing to one-half of a diopter, theoretically accommodation can provide only limited information about the distance to objects closer than 2 meters (Hochberg, 1971). In fact, accommodation does not appear to be used to judge distance directly but may be used indirectly in computing the sizes of nearby objects (Wallach & Floor, 1971).

Structure-from-Motion

When an object is in motion or when we ourselves move through the environment, the result is a dynamically changing pattern of light on the retina. Structure-from-motion information is generally divided into two different classes: motion parallax and kinetic depth effect. An example of motion parallax occurs when we look sideways out of a car or train window. Things nearby appear to be moving very rapidly, whereas objects close to the horizon appear to move gradually. Overall, there is a velocity gradient, as illustrated in Figure 7.22(a).

When we move forward through a cluttered environment, the result is a very different expanding pattern of motion, like that shown in Figure 7.22(b). Wann et al. (1995) showed that subjects were able to control their headings with an accuracy of 1 to 2 degrees when they were given feedback from a wide-screen field of dots through which they had to steer. There is also evidence for specialized neural mechanisms sensitive to the time to contact with a visual surface that is being approached. This is inversely proportional to the rate of optical expansion of the pattern of surface features (Lee & Young, 1985), a variable called *tau*.

The kinetic depth effect can be demonstrated with a wire bent into a complex 3D shape and projected onto a screen, as shown in Figure 7.22(c). Casting the shadow of the wire will suffice for the projection. The result is a two-dimensional line, but if the wire is rotated, the three-dimensional shape of the wire immediately becomes apparent (Wallach & O'Connell, 1953). The kinetic depth effect dramatically illustrates a key concept in understanding space perception. The brain generally assumes that objects are rigid in 3D space, and the mechanisms of object perception incorporate this constraint. The moving shadow of the rotating bent wire is perceived as a rigid 3D object, not as a wiggling 2D line. It is easy to simulate this in a computer graphics system by creating an irregular line, rotating it about a vertical axis, and displaying

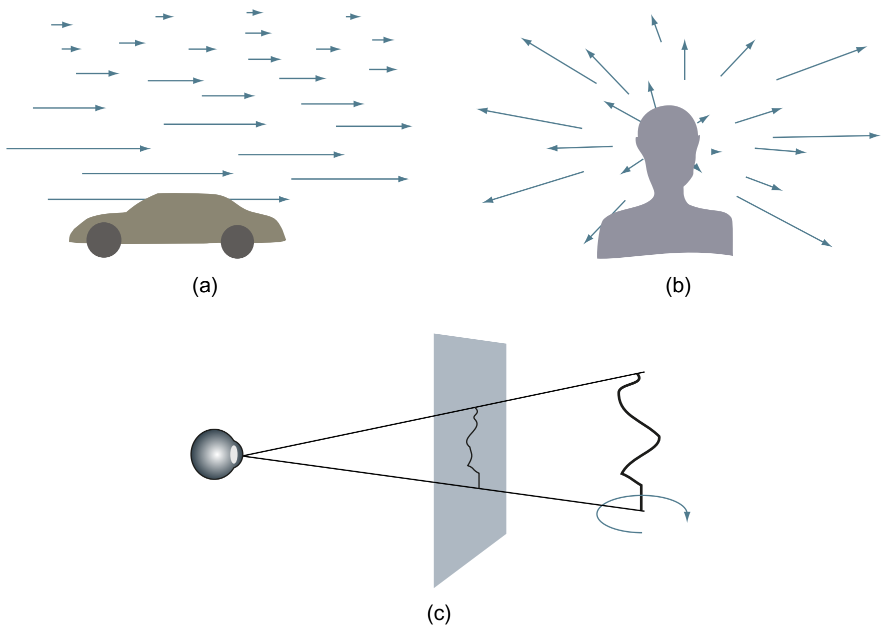


Figure 7.22 Three different kinds of structure-from-motion information. (a) The velocity gradient that results when the viewer is looking sideways out of a moving vehicle. (b) The velocity field that results when the viewer is moving forward through the environment. (c) The kinetic depth information that results when a rotating rigid object is projected onto a screen.

it using standard graphics techniques. Visualizations where many small discrete objects are arranged in space as well as 3D node–link structures can become much clearer with kinetic depth. Structure-from-motion is one reason for the effectiveness of fly-through animated movies that take an observer through a data space.

An obvious problem when using kinetic depth in data visualization is that people often wish to contemplate a structure from a particular viewpoint; rotating it causes the viewpoint to be continuously changed. This can be mitigated by having the scene rotate about a vertical axis. If the rotation is oscillatory, then the viewpoint can be approximately preserved.

> **[G7.5]** To help users understand depth relationships in 3D data visualizations, consider using structure-from-motion by rotating the scene around the center of interest. This is especially useful when objects are unattached to other parts of the scene.

Eye Convergence

When we fixate an object with both eyes, the eyes converge to a degree dictated by the distance of the object. This *vergence* angle is illustrated in Figure 7.23. Given the two line-of-sight vectors, it is a matter of simple trigonometry to determine the distance to the fixated object; however, the evidence suggests that the human brain is not good at this geometric computation except for objects within arm's length (Viguier et al. 2001). The vergence sensing system appears capable of quite rapid recalibration in the presence of other spatial information (Fisher & Cuiffreda, 1990).

Stereoscopic Depth

Stereoscopic depth is information about distance provided by the slight differences in images on the retinas of animals with two forward-looking eyes. Stereoscopic displays simulate these differences by presenting different images to the left and right eyes of viewers. There is an often expressed opinion that stereoscopic displays allow "truly" 3D images. In advertising literature, potential buyers are urged to buy stereoscopic

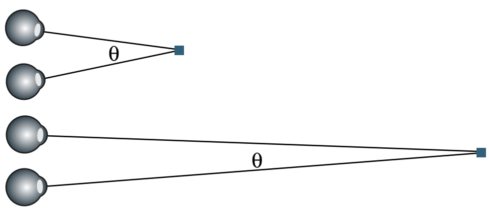


Figure 7.23 The vergence angle θ varies as the eyes fixate on near and far objects.

display equipment and "see it in 3D." As should be plain from this chapter, stereoscopic disparity is only one of many depth cues that the brain uses to analyze 3D space, and it is by no means the most useful one. If fact, as much as 20% of the population may be stereo blind, yet they function perfectly well and are often unaware that they have a disability. Nevertheless, stereoscopic displays can provide a particularly compelling sense of a 3D virtual space, and for a few tasks they can be extremely useful.

The basis of stereoscopic depth perception is forward-facing eyes with overlapping visual fields. On average, human eyes are separated by about 6.4 centimeters; this means that the brain receives slightly different images, which can be used to compute relative distances of pairs of objects. Stereoscopic depth is a technical subject, and we therefore begin by defining some of the terms.

Figure 7.24 illustrates a simple stereo display. Both eyes are fixated on the vertical line (*a* for the right eye, *c* for the left eye). A second line, *d*, in the left eye's image is fused with *b* in the right eye's image. The brain resolves the discrepancy in line spacing by perceiving the lines as being at different depths, as shown.

Angular disparity is the difference between the angular separation of a pair of points imaged by the two eyes (disparity = $\alpha - \beta$). *Screen disparity* is the distance between parts of an image on the screen (disparity = $[c - d] - [a - b]$).

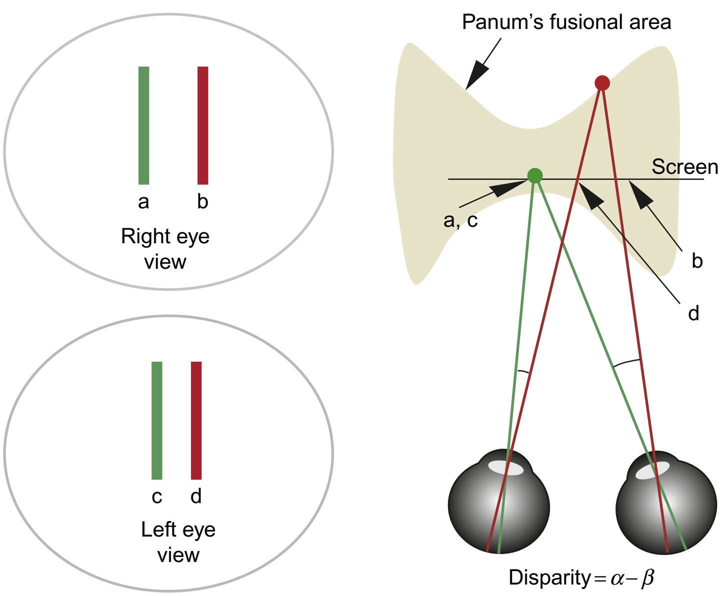


Figure 7.24 A simple stereo display. Different images for the two eyes are shown on the left. On the right, a top-down view shows how the brain interprets this display. The vertical lines *a* and *b* in the right-eye image are perceptually fused with *c* and *d*, respectively, in the left-eye image.

If the disparity between the two images becomes too great, double vision (called *diplopia*) occurs. Diplopia is the appearance of the doubling of part of a stereo image when the visual system fails to fuse the images. The 3D area within which objects can be fused and seen without double images is called *Panum's fusional area*. In the worst case, Panum's fusional area has remarkably little depth. At the fovea, the maximum disparity before fusion breaks down is only 1/10 degree, whereas at 6 degrees of eccentricity (of the retinal image from the fovea), the limit is 1/3 degree (Patterson & Martin, 1992). The reason why only small disparities can be handled is that disparity-detecting neurons in V1 are only capable of responding to small localized differences between the images from the two eyes (Qian & Zhu, 1997).

Stereopsis is a *superacuity*. We can resolve disparities of only 10 seconds of arc at better than chance. This means that under optimal viewing conditions we should be able to see a depth difference between an object at 1 kilometer and an object at infinity.

It is worthwhile to consider what these numbers imply for monitor-based stereo displays. A screen with 30 pixels per centimeter, viewed at 57 centimeters, will have 30 pixels per degree of visual angle. The 1/10 degree limit on the visual angle before diplopia occurs translates into about 3 pixels of screen disparity. This means that we can only display 3 whole-pixel-depth steps before diplopia occurs, either in front of or behind the screen, in the worst case. It also means it will only be possible to view a virtual image that extends in depth a fraction of a centimeter from the screen (assuming an object on the screen is fixated). But, it is important to emphasize that this is a worst-case scenario. It is likely that antialiased images will allow better than pixel resolution, for exactly the same reason that vernier acuities can be achieved to better than pixel resolution (discussed in Chapter 2). In addition, the size of Panum's fusional area is highly dependent on a number of visual display parameters, such as the exposure duration of the images and the size of the targets. Moving targets, simulated depth of focus, and greater lateral separation of the image components all increase the size of the fusional area (Patterson & Martin, 1992). Depth judgments based on disparity can also be made outside the fusional area, although these are less accurate.

Problems with Stereoscopic Displays

It is common for users of 3D visualization systems with stereoscopic display capabilities to disable stereo viewing once the novelty has worn off. There are a number of reasons why stereoscopic displays are disliked. Double-imaging problems tend to be much worse in stereoscopic computer displays than in normal viewing of the 3D environment. One of the principal reasons for this is that in the real world objects farther away than the one fixated are out of focus on the retina. Because we can fuse blurred images more easily than sharply focused images, this reduces diplopia problems in the real world. In addition, focus is linked to attention and foveal fixation. In the real world, double images of nonattended peripheral objects generally will not be noticed. Unfortunately, in present-day computer graphics systems, particularly those that allow for real-time interaction, depth of focus is rarely simulated. All parts of the computer graphics image are therefore equally in focus, even though some parts of the image may have large disparities. Thus, the double images that occur in stereoscopic computer graphics displays are very obtrusive unless depth of focus is simulated.

Frame Cancellation

Valyus (1966) coined the phrase *frame cancellation* to describe a common problem with stereoscopic displays. If the stereoscopic depth cues are such that a virtual image should appear in front of the screen, the edge of the screen appears to occlude the virtual object, as shown in Figure 7.25. Occlusion overrides the stereo depth information, and the depth effect collapses. This is typically accompanied by a double image of the object that should appear in front.

> **[G7.6]** When creating stereoscopic images, avoid placing graphical objects so that they appear in front of the screen and are clipped by the edges of the screen. The simplest way of doing this is to ensure that no objects are in front of the screen in terms of their stereoscopic depth.

The Vergence–Focus Problem

When we change our fixation between objects placed at different distances, two things happen: The convergence of the eyes changes (vergence), and the focal lengths of the lenses in the eyes accommodate to bring the new object into focus. The vergence and

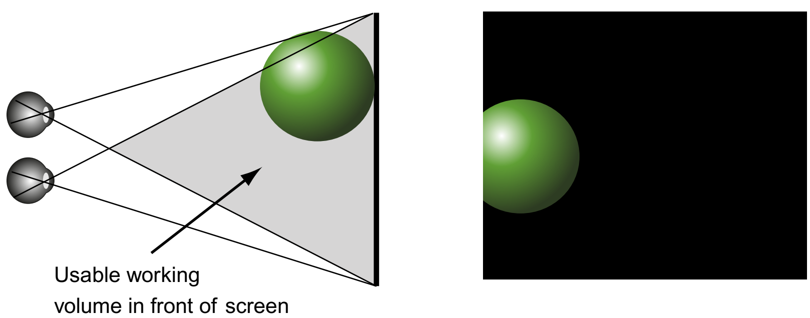


Figure 7.25 Frame cancellation occurs when stereoscopic disparity cues indicate that an object is in front of the monitor screen. Because the edge of the screen clips the object, this acts as an occlusion depth cue and the object appears to be behind the window, canceling the stereo depth effect. Because of this, the usable working volume of a stereoscopic display is restricted as shown.

the focus mechanisms are coupled in the human visual system. If one eye is covered, the vergence and the focus of the covered eye change as the uncovered eye accommodates objects at different distances; this illustrates vergence being driven by focus. The converse also occurs—a change in vergence can drive a change in focus.

In a stereoscopic display, all objects lie in the same focal plane, regardless of their apparent depth; however, accurate disparity and vergence information may fool the brain into perceiving them at different depths. Screen-based stereo displays provide disparity and vergence information, but no focus information. The failure to present focus information correctly, coupled with vergence, may cause a form of eyestrain (Wann et al., 1995; Mon-Williams & Wann, 1998).

This problem is present in both stereoscopic head-mounted systems and monitor-based stereo displays. Wann et al. (1995) concluded that vergence and focus cross-coupling "prevents large depth intervals of three-dimensional visual space being rendered with integrity through dual two-dimensional displays." This may account for the common reports of eyestrain occurring with dynamic stereoscopic displays. It is also worth noting that, because people lose the ability to refocus their eyes as they get older, this particular problem should decline with age.

Distant Objects

The problems with stereoscopic viewing are not always related to disparities that are too large. Sometimes disparities may be too small. The stereoscopic depth cue is most useful at 30 meters or less from the viewer. Beyond this, disparities tend to be too small to be resolved, except under optimal viewing conditions. For practical purposes, most useful stereoscopic depth is obtained within distances of less than 10 meters from the viewer and may be optimal for objects held roughly at arm's length.

Making Effective Stereoscopic Displays

Because stereoscopic depth perception is a superacuity, the ideal stereoscopic display should have very high resolution, much higher than the typical desktop monitor. On current monitors, the fine detail is produced by pixels, and in a stereoscopic display the pixilation of features such as fine lines will generate false binocular correspondences. High-resolution displays enable the presentation of fine texture gradients and hence disparity gradients that are the basis for stereoscopic surface shape perception.

> **[G7.7]** When creating stereoscopic displays for 3D visualizations, use the highest possible screen resolution, especially in a horizontal direction, and aim to achieve excellent spatial and temporal antialiasing.

There are also ways of mitigating the diplopia, frame cancellation, and vergence–focus problems described previously, although they will not be fully solved until displays that can truly simulate depth become commercially viable. All the solutions involve reducing screen disparities by artificially bringing the computer graphics imagery into the fusional area. Valyus (1966) found that the diplopia problems were acceptable if no more than 1.6 degrees of disparity existed in the display. Based on this, he proposed that the screen disparity should be less than 0.03 times the distance to the screen; however, this provides only about ±1.5 centimeters of useful depth at normal viewing distances. Using a more relaxed criterion, Williams and Parrish (1990) concluded that a practical viewing volume falls between –25% and +60% of the viewer-to-screen distance. This provides a more usable working space.

One obvious solution to the problems involved in creating useful stereoscopic displays is simply to create small virtual scenes that do not extend much in front of or behind the screen. In many situations, though, this is not practical—for example, when we wish to make a stereoscopic view of extensive terrain. A more general solution is to compress the range of stereoscopic disparities so that they lie within a judiciously enlarged fusional area, such as that proposed by Williams and Parrish. A method for doing this is described in the next two sections.

Before going on, we must consider another potential problem. We should be aware that tampering with stereoscopic depth may cause us to misjudge distance. There is conflicting evidence as to whether this is likely. Some studies have shown stereoscopic disparity to be relatively unimportant in making *absolute* depth judgments. Using a special apparatus, Wallach and Karsh (1963) found that when they rotated a wire-frame cube viewed in stereo, only half of the subjects were even aware of a doubling in their eye separation. Because increasing eye separation increases stereo disparities, this should have resulted in a grossly distorted cube. The fact that distortion was not perceived indicates that kinetic depth-effect information and rigidity assumptions are much stronger than stereo information. Ogle (1962) argued that stereopsis gives us information about the relative depths of objects that have small disparities especially when they are close together. When it comes to judging the overall layout of objects in space, other depth cues dominate. Also, many experiments show large individual differences in how we use the different kinds of depth information, so we will never have a simple one-size-fits-all account.

Overall, we can conclude that the brain is very flexible in weighing evidence from the different depth cues and that disparity information can be scaled by the brain depending on other available information. Therefore, it should be possible to artificially manipulate the overall pattern of stereo disparities and enhance local 3D space perception without distorting the overall sense of space, if other strong cues to depth, such as linear perspective, are provided. We (Ware et al., 1998) investigated dynamically changed disparities by smoothly varying the stereoscopic eye separation parameter. We found that a subject's disparity range could be changed by about 30% over a 2-second interval, without him or her even noticing, as long as the change was smooth.

[G7.8] When creating stereoscopic displays for 3D visualizations, adjust the virtual eye separation to optimize perceived stereoscopic depth while minimizing diplopia.

Cyclopean Scale

One simple method that we developed to deal with diplopia problems is called a *cyclopean scale* (Ware et al., 1998). As illustrated in Figure 7.26, this manipulation involves scaling the virtual environment about the midpoint between the observer's estimated eye positions (where the Cyclops of mythology had his one eye). The scaling variable is chosen so that the nearest part of the scene comes to a point just behind the monitor screen. To understand the effects of this operation, consider first that scaling a virtual world about a *single* viewpoint does not result in any change in computer graphics imagery (assuming depth of focus is not taken into account). Thus, the cyclopean scale does not change the overall sizes of objects as they are represented on a computer screen. It does change disparities, though. The cyclopean scale has a number of benefits for stereo viewing: More distant objects, which would normally not benefit from stereo viewing because they are beyond the range where significant disparities exist, are brought into a position where usable disparities are present. The vergence–focus discrepancy is reduced. At least for the part of the virtual object that lies close to the screen, there is no vergence–focus conflict. Virtual objects that are closer to the observer than to the screen are also scaled so they lie behind the screen. This removes the possibility of frame cancellation.

Virtual Eye Separation

The cyclopean scale, although useful, does not remove the possibility of disparities that result in diplopia. In order to do so, it is necessary to compress or expand the disparity range. To understand how this can be accomplished, it is useful to consider a device called a *telestereoscope* (Figure 7.27). A telestereoscope is generally used to increase disparities when distant objects are viewed, but the same principle can also

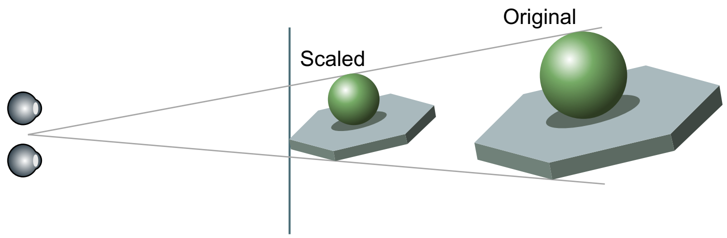


Figure 7.26 Cyclopean scale: A virtual environment is resized around a center point, midway between the left and right viewpoints.

be used to decrease the range of disparities by optically moving the eyes closer together. Figure 7.28 illustrates the concept of virtual eye separation and demonstrates how the apparent depth of an object decreases if the virtual viewpoints have a wider eye separation than the actual viewpoint. We consider only a single point in the virtual space. If E_v is the virtual eye separation and E_a is the actual eye separation of an observer, the relationship between depth in the virtual image (Z_v) and in the viewed stereo image (Z_s) is a ratio:

$$\frac{E_v}{E_a} = \frac{Z_s(Z_v + Z_e)}{Z_v(Z_s + Z_e)} \tag{7.1}$$

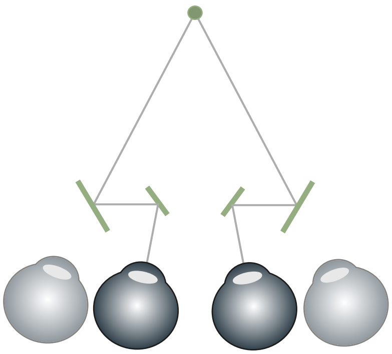


Figure 7.27 A telestereoscope is a device that uses mirrors or prisms to increase the effective eye separation, thereby increasing stereoscopic depth information (disparities).

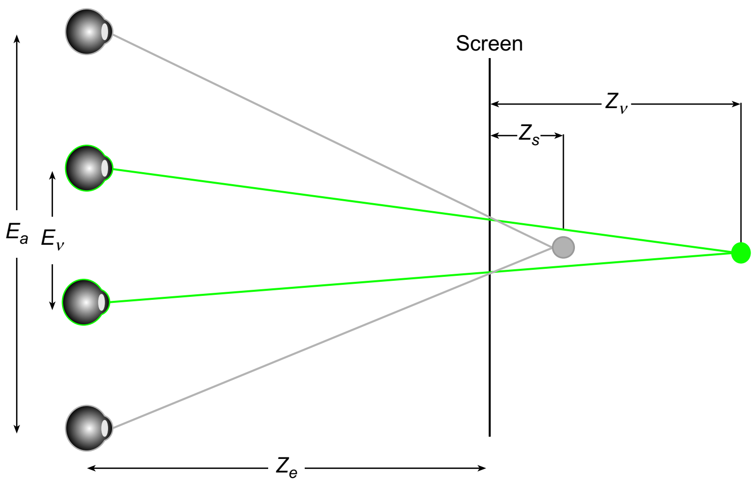


Figure 7.28 The geometry of virtual eye separation. In this example, the stereoscopic depth is decreased by computing an image with a virtual eye separation that is smaller than the actual eye separation.

where Z_e represents the distance to the screen. By rearranging terms, we can get the stereo depth expressed as a function of the virtual depth and the virtual eye separation:

$$Z_s = \frac{Z_e Z_v E_v}{E_a z_v + E_a Z_e - E_v Z_v} \tag{7.2}$$

Stereoscopic depth can just as easily be increased. If the virtual eye separation is smaller than the actual eye separation, stereo depth is decreased. If the virtual eye separation is larger than the actual eye separation, stereo depth is increased. $E_v = E_a$ for "correct" stereoscopic viewing of a virtual scene, although for the reasons stated this may not be useful in practice. When $E_v = 0.0$, both eyes get the same image, as in single viewpoint graphics. Note that stereo depth and perceived depth are not always equal. The brain is an imperfect processor of stereo information, and other depth cues may be much more important in determining the perceived depth. Experimental evidence shows that subjects given control of their eye-separation parameters have no idea what the "correct" setting should be (Ware et al., 1998). When asked to adjust the virtual eye-separation parameter, subjects tended to decrease the eye separation for scenes in which there was a lot of depth, but actually increased eye separation beyond the normal (enhancing the sensation of stereoscopic depth) when the scene was flat. This behavior can be mimicked by an algorithm designed to test automatically the depth range in a virtual environment and adjust the eye-separation parameters appropriately (after cyclopean scale). We have found the following function to work well for a large variety of digital terrain models. It uses the ratio of the nearest point to the farthest point in the scene to calculate the virtual eye separation in centimeters.

$$\mathit{Eye\,Separation} = 2.5 + 5.0 * (\mathit{Near\,Point}/\mathit{Far\,Point})^2 \tag{7.3}$$

This function increases the eye separation to 7.5 cm for shallow scenes (as compared to a normal value of 6.4 cm) and reduces it to 2.5 cm for very deep scenes.

Artificial Spatial Cues

There are effective ways to provide information about space that are not based directly on the way information is provided in the normal environment, although the best methods are probably effective because they make use of existing perceptual mechanisms. One common technique used to enhance 3D scatterplots is illustrated in Figure 7.29. A line is dropped from each data point to the ground plane. Without these lines, only a 2D judgment of spatial layout is possible. With the lines, it is possible to estimate 3D position. Kim et al. (1991) showed that this artificial spatial cue can be at least as effective as stereopsis in providing 3D position information. It should be understood that, although the vertical line segments in Figure 7.29 can be considered artificial additions to the plot, there is nothing artificial about the way they operate as depth cues. Gibson (1986) pointed out that one of the most effective ways to estimate the sizes of objects is with reference to the ground plane. Adding the vertical lines creates a link to the ground plane and the rich texture size and linear

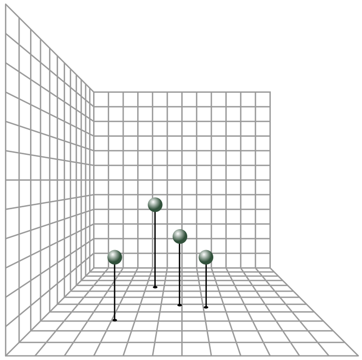


Figure 7.29 Dropping lines to a ground plane is an effective artificial spatial cue.

perspective cues embedded in it. In this respect, drop lines function in the same way as cast shadows, but they are generally easier to interpret and should result in more accurate judgments, given that cast shadows can be confusing with certain lighting directions.

[G7.9] In 3D data visualizations where a strong, preferably gridded, ground plane is available, consider using drop lines to add depth information for small numbers of discrete isolated objects.

Sometimes in computer graphics, foreground objects and objects behind them have the same color, causing them to visually fuse, which nullifies the occlusion cue. A technique has been developed that artificially enhances occlusion by putting a *halo* along the occluding edges of the foreground objects (see Figure 7.30). Perception of occlusion relies on edge contrast and the continuity of an overlaying contour, and this depends on neural mechanisms for edge detection, but artificial enhancement can amplify these factors to a degree that rarely if ever occurs in nature.

[G7.10] In 3D data visualizations, consider using halos to enhance occlusion where this is an important depth cue and where overlapping objects have the same color or minimal luminance difference.

Computer graphics systems sometimes provide a function to implement what researchers call *proximity luminance covariance* (Dosher et al., 1986). This function is confusingly called *depth cueing* in computer graphics texts. Depth cueing in computer graphics is the ability to vary the color of an object depending on its distance from the viewpoint, as illustrated in Figure 7.31. Normally, more distant objects are faded toward the background color, becoming darker if the background is dark and lighter if the background is light.

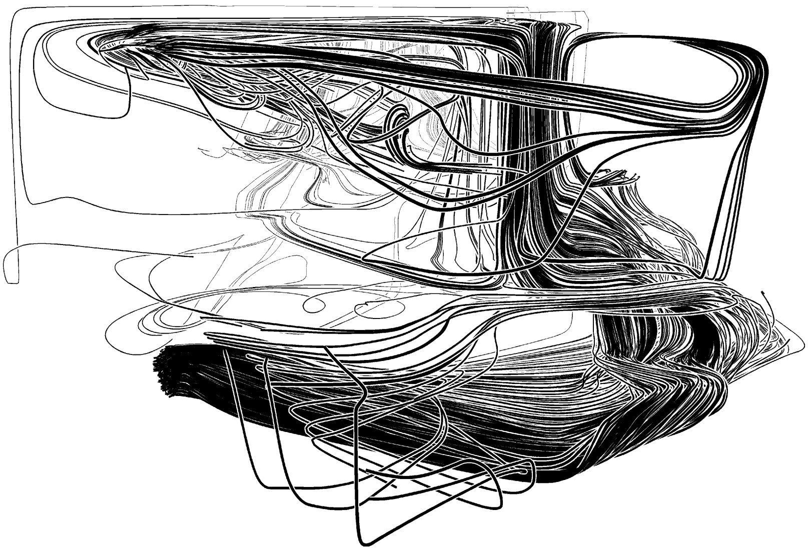


Figure 7.30 This figure shows a set of streamlines for airflow around a room. The principal depth cue is occlusion. The occlusion cue has been artificially enhanced by "halos" in the form of white borders on the black streamlines. (*From* Everts et al. (2009). *Reproduced with permission.*)

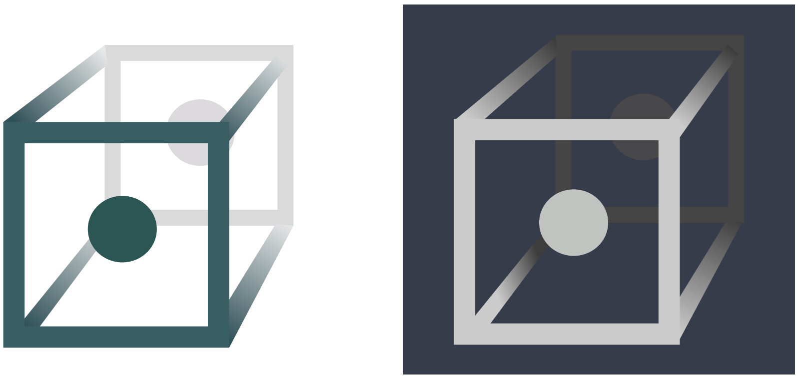


Figure 7.31 Proximity luminance contrast covariance as a depth cue. The contrast with the background is reduced with distance. This simulates extreme atmospheric effects.

This cue is better named *proximity luminance contrast covariance*, because it is contrast, not luminance, that produces the depth impression. Proximity contrast covariance simulates an environmental depth cue sometimes called *atmospheric depth*. This refers to the reduction in contrast of distant objects in the environment, especially under hazy viewing conditions. The depth cueing used in computer graphics is generally much more extreme than any atmospheric effects that occur in nature, and for this reason it can be considered an "artificial" cue. Dosher et al. (1986) showed that contrast covariance could function as an effective depth cue but was weaker than stereo for static displays.

Depth Cues in Combination

In designing a visualization, the designer has considerable freedom to choose which depth cues to include and which to leave out. One might think it best to simply include all the cues, just to be sure, but in fact this is not the best solution in most cases. There can be considerable costs associated with creating a stereoscopic display, for example, or with using real-time animation to take advantage of structure-from-motion cues. The hardware is more expensive, and a more complex user interface must be provided. Some cues, such as depth-of-focus information, are difficult or impossible to compute in the general case, because without knowing what object the observer is looking at, it is impossible to determine what should be shown in focus and what should be shown out of focus. A general theory of space perception should make it possible to determine which depth cues are likely to be most valuable. Such a theory would provide information about the relative values of different depth cues when they are used in combination.

Unfortunately, there is no single, widely accepted unifying theory of space perception, although the issue of how depth cues interact has been addressed by a number of studies; for example, the weighted-average model assumes that depth perception is a weighted linear sum of the depth cues available in a display (Bruno & Cutting, 1988). Alternatively, depth cues may combine in a geometric sum (Dosher et al., 1986). Young et al. (1993) proposed that depth cues are combined additively but are weighted according to their apparent reliability in the context of other cues and relevant information. There is also evidence that some depth cues—in particular, occlusion—work in a logical binary fashion rather than contributing to an arithmetic or geometric sum. For example, if one object overlaps another in the visual image, it is perceived as closer to the observer regardless of what the other cues indicate.

Most of the work on spatial information implicitly contains the notion that all spatial information is combined into a single cognitive model of the 3D environment and that this model is used as a resource in performing all spatial tasks. This theoretical position is illustrated in Figure 7.32. Evidence is accumulating, however, that this unified model of cognitive space is fundamentally flawed.

The alternative theory that is emerging is that depth cues are combined expeditiously, depending on task requirements (Jacobs & Fine 1999; Bradshaw et al., 2000); for example, Wanger et al. (1992) showed that cast shadows and motion parallax cues both helped in the task of orienting one virtual object to match another. Correct linear perspective (as opposed to parallel orthographic perspective) actually increased errors; it acted as a kind of negative depth cue for this particular task. With a different task, that of translating an object, linear perspective was found to be the most useful of the cues,

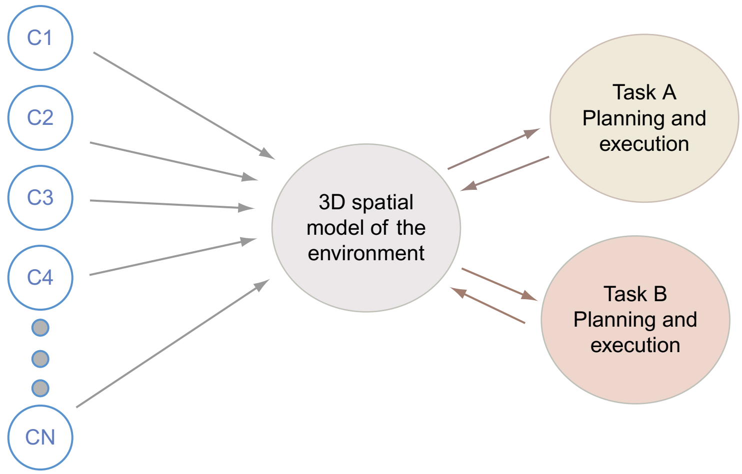


Figure 7.32 Most models of 3D space perception assume that depth cues (C1, … , CN) feed into a cognitive 3D model of the environment. This, in turn, is used as a resource in task planning and execution.

and motion parallax did not help at all. Further, Bradshaw et al. (2000) showed that stereopsis is critical in setting objects at the same distance from the observer, but motion parallax is more important for a layout task involving the creation of a triangle laid out in depth.

This alternative task-based model of depth perception is illustrated in Figure 7.33. It does not assume an internal cognitive 3D model of the environment. Instead, cues are combined with different weightings depending on the task. Whatever the task (for example, threading a needle or running through a forest), certain depth cues are informative and other cues can be irrelevant.

An application designer's choice is not whether to design a 3D or 2D interface, but rather which depth cues to use to best support a particular set of tasks. Depth cues can be applied somewhat independently. In a static picture, for example, we use all of the monocular pictorial depth cues, but not motion parallax or stereoscopic disparity. If we add structure-from-motion information, we get what we see at the movie theater. If we add stereo to a static picture, the result is the kind of stereoscopic viewer popular in Victorian times. We can also use far fewer depth cues. Modern desktop GUIs only use occlusion for windows, some minor shading information to make the menus and buttons stand out, and a cast shadow for the cursor.

There are some restrictions on our freedom to arbitrarily choose combinations of depth cues because some cues depend on the correct implementation of other cues. Figure 7.34 shows a dependency graph for depth cues. An arrow means that a particular cue depends on another cue to appear correctly. This graph does not show absolute rules that cannot be broken, but it does imply that breaking the rules will have undesirable

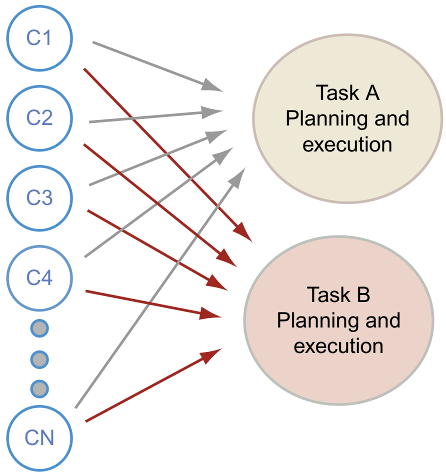


Figure 7.33 Experimental evidence suggests that depth cues (C1, … , CN) are weighted very differently for different tasks, suggesting that there is no unified cognitive spatial model.

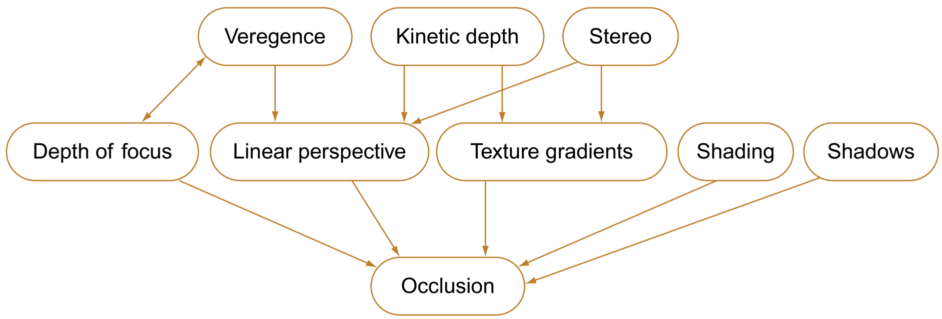


Figure 7.34 A dependency graph for depth cues. Arrows indicate how depth cues depend on each other for undistorted appearance.

consequences; for example, the graph shows that kinetic depth depends on correct perspective. It is possible to break this rule and show kinetic depth with a parallel (orthographic) perspective. The undesirable consequence is that a rotating object will appear to distort as it rotates. This graph is transitive; all of the depth cues depend on occlusion being shown properly, because they all depend on something that in turn depends on occlusion. Occlusion is, in a sense, the most basic depth cue; it is difficult to break the occlusion dependency rule and have a perceptually coherent scene.

[G7.11] In 3D data visualizations, understand and use the depth cues that are most important for the critical tasks in an application. Implement other cues on which these critical cues depend.

Task-Based Space Perception

The obvious advantage of a theory of space perception that takes the task into account is that it can be directly applied to the design of interactive 3D information displays. The difficulty is that the number of tasks is potentially large, and many tasks that appear at first sight to be simple and unified are found, upon more detailed examination, to be multifaceted. Nevertheless, taking the task into account is essential; perception and action are intertwined. If we are to understand space perception, we must understand the purpose of perceiving.

The best hope for progress lies in identifying a small number of elementary tasks requiring depth perception that are as generic as possible. If the particular set of spatial cues associated with each task can be characterized, then the results can be used to construct design guidelines. The remainder of this chapter is devoted to analyzing the following tasks:

- Tracing paths in 3D graphs
- Judging the morphology of surfaces
- Finding patterns of points in 3D space
- Finding shapes of 3D trajectories
- Judging the relative positions of objects in space
- Judging the relative movements of self within the environment
- Reaching for objects
- Judging the "up" direction
- Feeling a sense of presence

This list of nine tasks is at best only a beginning; each has many variations, and none turns out to be particularly simple in perceptual terms.

Tracing Data Paths in 3D Graphs

Many kinds of information structures can be represented as networks of nodes and arcs, technically called *graphs*. Figure 7.35 shows an example of object-oriented computer software represented using a 3D graph. Nodes in the graph stand for various kinds of entities, such as modules, classes, variables, and methods. The 3D spars that connect the entities represent various kinds of relationships characteristic of object-oriented software, such as inheritance, function calls, and variable usage. Information structures are becoming so complex that there has been considerable interest in the question of whether a 3D visualization will reveal more information than a 2D visualization. Is it a good idea?

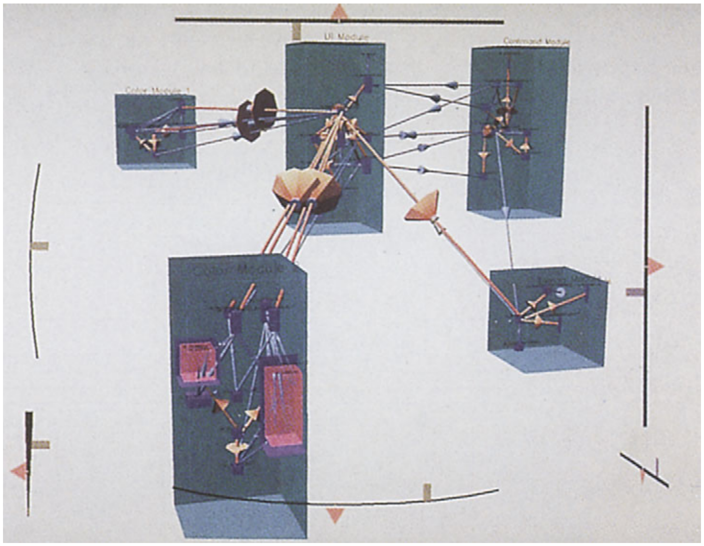


Figure 7.35 The structure of object-oriented software code is represented as a graph in 3D.

One special kind of graph is a tree. Trees are a standard technique for representing hierarchical information, such as organizational charts or the structure of information in a computer directory. The cone tree is a graphical technique for representing tree-graph information in 3D (Robertson et al., 1993). It shows the tree branches arranged around a series of circles, as illustrated in Figure 7.36. The inventors of the cone tree claim that as many as 1000 nodes may be displayed without visual clutter using cone trees, clearly more than could be contained in a 2D layout; however, with a cone tree, we do not see all 1000 nodes at a time, as some are hidden and parts of the tree must be rotated to reveal them. In addition, 3D cone trees require more complex and time-consuming user interactions to access nodes than are necessary for 2D layouts, so the task of tracing out a path will take longer to perform. Other 2D methods such as the hyperbolic tree (Lamping et al., 1995) have proven to be more efficient.

Empirical evidence shows that the number of errors in detecting paths in 3D tree structures is substantially reduced if stereoscopic and motion depth cues are used. Sollenberger and Milgram (1993) investigated a task involving two 3D trees with intermeshed branches. The task was to discover to which of two tree roots a highlighted leaf was attached. Subjects carried out the task both with and without stereo depth, and with and without rotation to provide kinetic depth. Their results showed that both stereo and kinetic depth viewing reduced errors, but that kinetic depth was the more potent cue. However, an abstract tree structure is not necessarily a good candidate for 3D visualization, for the reason that a tree data structure can always be laid out on a 2D plane in such a way that none of the paths cross (path crossings are the main reason for errors in path-tracing tasks), so creating a 2D visualization is easy for trees.

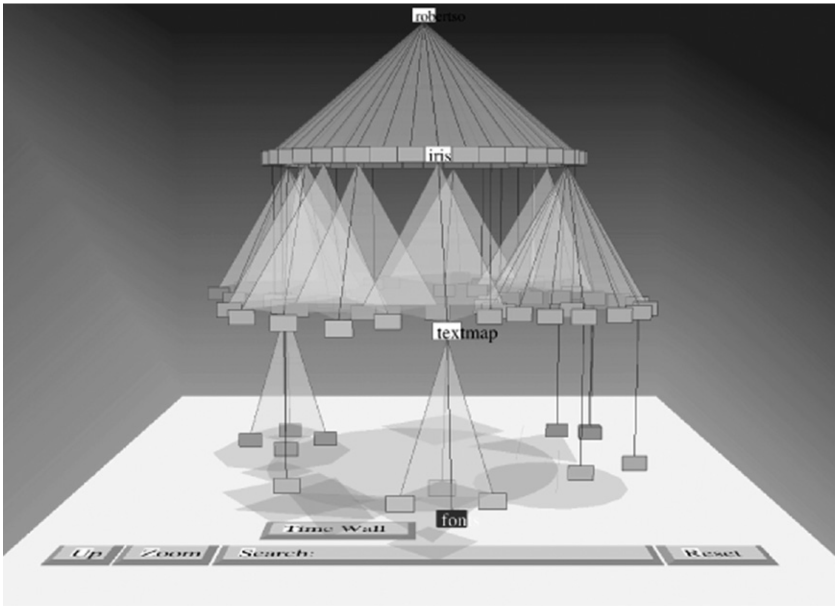


Figure 7.36 The cone tree invented by Robertson et al. (1993).

Unlike trees, more general node–link structures, such as directed acyclic graphs, usually cannot be laid on a plane without some links crossing and these are a better test of whether 3D viewing allows more information to be seen. To study the effects of stereo and kinetic depth cues on 3D visualization of complex node–link structures, we systematically varied the size of a graph laid out in 3D and measured path-tracing ability with both stereoscopic and motion depth cues (Ware & Franck, 1996). Our results, illustrated in Figure 7.37, showed a factor of 1.6 increase in the complexity that could be viewed when stereo was added to a static display, but a factor of 2.2 improvement when kinetic depth cues were added. A factor of 3.0 improvement occurred with both stereo and kinetic depth cues. These results held for a wide range of graph sizes. A subsequent experiment showed that the advantage of kinetic depth cues applied whether the motion was coupled to movements of the head or movements of the hand or consisted of automatic oscillatory rotation of the graph.

Having a higher resolution screen can increase the benefit of stereo and motion cues. We found an order of magnitude benefit to 3D viewing using an ultra-high-resolution stereoscopic display and found that subjects were rapidly and accurately able to resolve paths in graphs with more than 300 nodes (Ware & Mitchell, 2008).

Occlusion is one additional depth cue that should make it easier to differentiate links in 3D graphs, but if all the links are uniformly colored the depth ordering will not be visible. Coloring the links differently or using halos like those shown in Figure 7.30 should help (Telea & Ersoy, 2010).

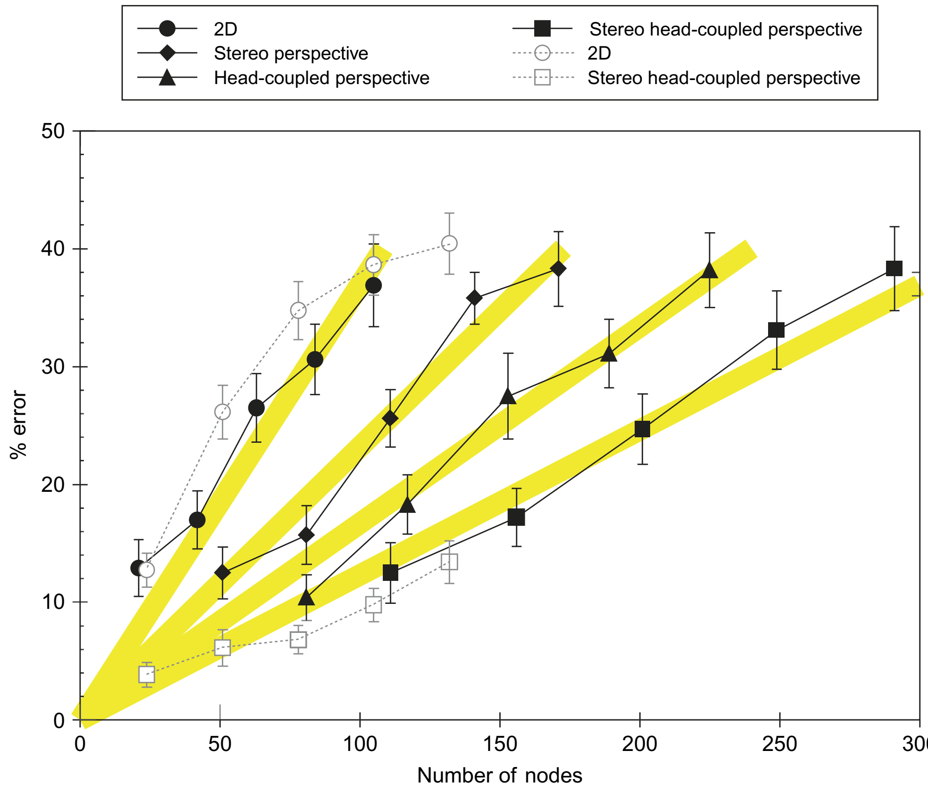


Figure 7.37 The plot shows that errors increased when the number of nodes increased, with and without stereo and/or motion parallax. The task involved tracing paths in a 3D graph (Ware & Franck, 1996).

It seems unlikely that other depth cues will contribute much to a path-tracing task. There is no obvious reason to expect perspective viewing to aid the comprehension of connections between nodes in a 3D graph, and this was confirmed empirically by our study (Ware & Franck, 1996). There is also no reason to suppose that shading and cast shadows would provide any significant advantage in a task involving connectivity, although shading might help in revealing the orientation of the arcs.

[G7.12] When it is critical to perceive large 3D node–link structures, consider using motion parallax, stereoscopic viewing, and halos.

Still, interacting with nodes is a common requirement for graph-based visualization; often nodes must be selected to get related information. This is usually more difficult and costly with a 3D interface, making 2D network visualization methods a better choice. An alternative to 3D viewing is to use 2D interaction techniques to gain access to larger graphs. We consider these alternatives in Chapter 10.

Judging the Morphology of Surfaces

From a Gibsonian point of view, the obvious way to represent a univariate map is to make it into a physical surface in the environment. Some researchers occasionally do just this; they construct plaster or foam models of data surfaces. But, the next best thing may be to use computer graphics techniques to shade the data surface with a simulated light source and give it a simulated color and texture to make it look like a real physical surface. Such a simulated surface can be viewed using a stereoscopic viewing apparatus, by creating different perspective images, one for each eye. These techniques have become so successful that the auto industry is using them to design car bodies in place of the full-size clay models that were once constructed by hand to show the curves of a design. The results have been huge cost savings and a considerably accelerated design process.

Four principal sets of visual cues for surface shape perception have been studied: shading models, surface texture, stereoscopic depth, and motion parallax. To determine which of these are the most effective, Norman et al. (1995) used computer graphics to render smoothly shaded rounded objects under various viewing conditions both with and without texture. They manipulated the entire list of variables given above—specular shading, Lambertian shading, texture, stereo, and motion parallax—in a multifactor experiment. Stereo and motion were studied only in combination with the other cues, because without shading or texture neither stereo nor motion cues can be effective.

Norman et al. (1995) found all of the cues they studied to be useful in perceiving surface orientation, but the relative importance of the cues differed from one subject to another. For some subjects, motion appeared to be the stronger cue; for others, stereo was stronger. A summary of their results with motion and stereo data combined is given in Figure 7.38. Motion and stereo both reduced errors dramatically when used in combination with any of the surface representations. Overall, the combination of shading (either specular or Lambertian) with either stereo or motion was either the best or nearly the best combination for all the subjects.

There have been other studies of the relative importance of different cues to the perception of surface shape. Todd and Mingolla (1983) found surface texture to be more effective in determining surface shape than either Lambertian shading or specular shading; however, because of the lack of a convincing general theory for the combination of spatial cues, it is difficult to generalize from experiments such as this. Many of the results may be valid only for specific textures conforming to a surface in a particular way (Kim et al., 1993; Interrante et al., 1997). For these reasons, it is not meaningful to make general statements such as, "Lambertian shading is more useful than texture." The values of the different cues will also depend on the nature of the surface features that are important and the particular texture used.

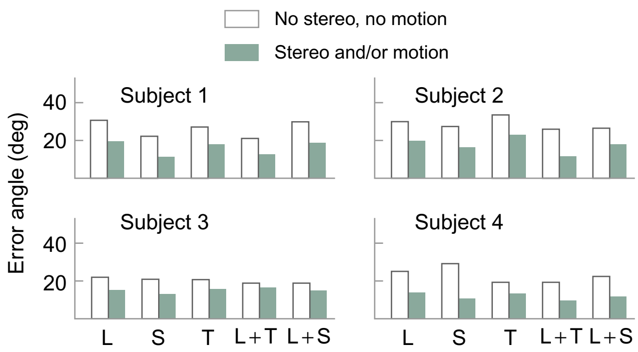


Figure 7.38 Results of the study of shape perception by Norman et al. (1995). The average errors in adjusted orientation are shown for five different surface representations. The different representations are labeled as follows: (L) Lambertian shading, (S) specular highlight shading, (T) texture with no shading, (L + T) Lambertian shading with texture, and (L + S) Lambertian shading with specular highlights. The four sets of histograms represent results from four different subjects.

Conformal Textures

The boundary contours of objects can interact with surface shading to change dramatically the perception of surface shape. Figure 7.39 is adapted from Ramachandran (1988). It shows two shapes that have exactly the same shading but different silhouette contours. The combination of silhouette contour information with shading information is convincing in both cases, but the surface shapes that are perceived are very different. This tells us that shape-from-shading information is inherently ambiguous; it can be interpreted in different ways, depending on the contours.

Contours that are drawn on a shaded surface can also drastically alter the perceived shape of that surface. Figure 7.40 has added shaded bands that provide internal contour information. As in Figure 7.39, the actual pattern of shading within each of the two images is the same. It is the contour information that makes one surface shape appear so different from the other. This technique can be used directly in displaying shaded surfaces to make a shape easier to perceive.

One of the most common ways to represent surfaces is to use a contour map. A contour map is a plan view representation of a surface with isoheight contours, usually spaced at regular intervals. Conceptually, each contour can be thought of as the line of intersection of a horizontal plane with a particular value in a scalar height field, as illustrated in Figure 7.41. Although reading contour maps is a skill that requires practice and experience, contour maps should not necessarily be regarded as entirely arbitrary graphical conventions. Contours are visually ambiguous with respect to such things as direction of slope; this information is given only in the printed labels that are attached to them. However, it is likely that the contours in contour maps get at least some of their expressive power because they provide perceptual shape and depth cues. As we have seen,

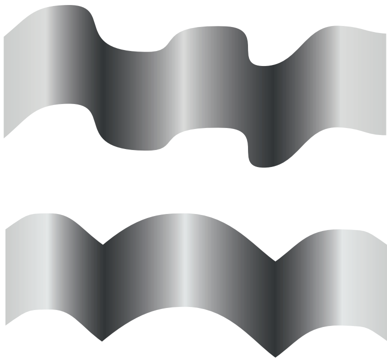


Figure 7.39 When scanned from left to right, the sequences of gray values in these two patterns are identical. The external contour interacts with the shading information to produce the perception of two very differently shaped surfaces. (*Redrawn from Ramachandran (1988).*)

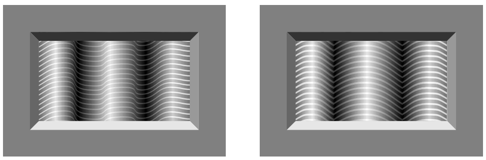


Figure 7.40 The left-to-right gray sequences in these patterns are identical. The internal contours interact with the shading information to produce the perception of two very differently shaped surfaces.

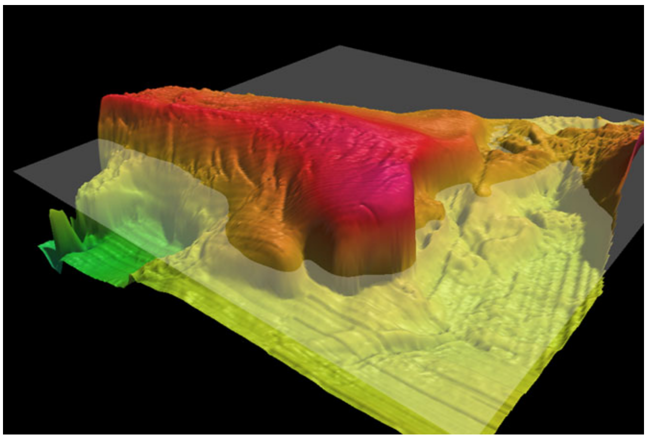


Figure 7.41 A contour is created by the intersection of a plane with a scalar field.

both occluding (silhouette) contours and surface contours are effective in providing shape information. Contours provide a form of conformal texture, giving both shape and slope information. Contour maps are a good example of a hybrid code; they make use of a perceptual mechanism, and they are partly conventional. The combination of contours with shading can be especially effective (Figure 7.42).

Texturing surfaces is important when they are viewed stereoscopically. This becomes obvious if we consider that a uniform nontextured polygon contains no internal stereoscopic information about the surface it represents. Under uniform lighting conditions, such a surface also contains no orientation information. When a polygon is textured, every texture element provides stereoscopic depth information relative to neighboring points. Figure 7.43 shows a stereoscopic pair of images representing a textured surface.

Figure 7.42 Shading provides the overall shape of the topography, but the contours provide both precise height information and supplementary shape and gradient information. (*From Google. With permission.*)

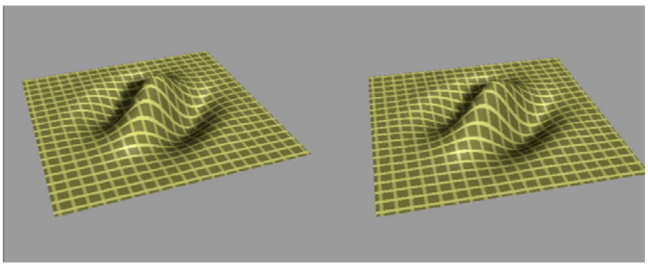


Figure 7.43 Texture is important in stereo viewing because it provides high-resolution disparity gradients, which in turn provide essential information to the disparity-sensing mechanisms of the visual cortex.

Stereoscopic viewing also considerably enhances our ability to see one surface through another, semitransparent, one (Interrante et al., 1997; Bair et al., 2009).

Guidelines for Displaying Surfaces

Taken together, the evidence suggests that to represent a surface clearly it may be possible to do better than simply creating a photorealistic rendering of a scene using the most sophisticated techniques of computer graphics. A simplified lighting model—for example, a single light source located at infinity—may be more effective than complex rendering using multiple light sources. The importance of contours and the easy recognizability of cartoon representation suggest that an image may be enhanced for display purposes by using techniques that are nonrealistic. Taking all these caveats into consideration, some guidelines may be useful for the typical case (the first four are restatements of G2.1, G2.2, G2.3, and G2.4 given in Chapter 2): *[G2.1] A simple lighting model, based on a single light source applied to a Lambertian surface, is a good default. The light source should be from above and to one side and infinitely distant. [G2.2] Specular reflection is especially useful in revealing fine surface detail. Because specular reflection depends on both the viewpoint and the position of the light source, the user should be given interactive control of both the lighting direction and the amount of specular reflection to specify where the highlights will appear. [G2.3] Cast shadows should be used, but only if the shadows do not interfere with other displayed information. The shadows should be computed to have blurred edges to make a clear distinction between shadow and surface pigment changes. [G2.4] Both Lambertian and moderate specular surface reflection should be modeled. More sophisticated lighting modeling, such as using the radiosity method, may help in the perception of occlusion and be useful in cases where other cues provide weak information.*

[G7.13] Consider using textures to help reveal surface shapes, especially if they are to be viewed in stereo. This is only appropriate for relatively smooth surfaces and where texture is not needed for some other attribute. Ideally, texturing should be low contrast so as not to interfere with shading information. Textures that have linear components are more likely to reveal surface shape than textures with randomly stippled patterns. When one 3D surface is viewed over another, the top surface should have lacy, see-through textures.

[G7.14] Consider using both structure-from-motion (by rotating the surface) and stereoscopic viewing to enhance the user's understanding of 3D shape in a 3D visualization. These cues will be especially useful when one textured transparent surface overlays another.

There are also temporal factors to be considered if viewing times are brief. When we are viewing stereoscopic displays, it can take several seconds for the impression of depth to build up. However, stereoscopic depth and structure-from-motion information interact strongly. With moving stereoscopic displays, the time to fusion can be considerably shortened (Patterson & Martin, 1992). In determining the shape of surfaces made from random dot patterns, using both stereoscopic and motion depth cues, Uomori and Nishida (1994) found that kinetic depth information dominated the initial perception of surface shape, but after an interval of 4 to 6 seconds, stereoscopic depth came to dominate.

Bivariate Maps—Lighting and Surface Color

In many cases, it is desirable to represent more than one continuous variable over a plane. This representation is called a *bivariate* or *multivariate map*. From the ecological optics perspective discussed in Chapter 1, the obvious bivariate map solution is to represent one of the variables as a shaded surface and the other as color coding on that surface. A third variable might use variations in the surface texture. These are the patterns we have evolved to perceive. An example is given in Figure 7.44, where one variable is a height map of the ocean floor and the surface color represents sonar backscatter strength. In this case, the thing being visualized is actually a physical 3D surface; however, the technique also works when both variables are abstract. A radiation field, for example, can be expressed as a shaded height map, and a temperature field can be represented by the surface color.

If this colored and shaded surface technique is used, some obvious tradeoffs must be observed. Because luminance is used to represent shape-from-shading by artificially illuminating the surface, we should minimally use luminance variation in coloring the surface. The surface coloring should be done mainly using the chromatic opponent channels discussed in Chapter 4. But, because of the inability of color to carry high-spatial-frequency information, only relatively gradual changes in color can be perceived; therefore, in designing a multivariate surface display, rapidly changing information should always be mapped to luminance. For a more detailed discussion of these spatial tradeoffs, see Robertson and O'Callaghan (1988), Rogowitz and Treinish (1996), and Chapter 4 of this book.

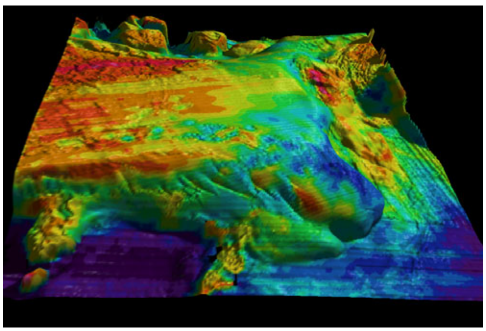


Figure 7.44 A bivariate map showing part of the Stellwagen Bank National Marine Sanctuary. One variable shows angular response of sonar backscatter, color coded and draped on the depth information given through shape-from-shading. (*From Mayer et al. (1997). Courtesy of Larry Mayer.*)

A similar set of constraints applies to the use of visual texture. Normally, it is advisable to use luminance contrast in displaying texture, but this will also tend to interfere with shape-from-shading information. If we use texture to convey information, we have less available visual bandwidth to express surface shape and surface color. We can gain a relatively clear and easily interpreted trivariate map, but only so long as we do not need to express a great deal of detail. Using color, texture, and shape-from-shading to display different continuous variables does not increase the total amount of information that can be displayed per unit area, but it does allow multiple map variables to be independently perceived.

[G7.15] As a method for displaying bivariate scalar field maps, use a shaded height field for one variable and color coding for the other. This will work best if the shaded variable is relatively smooth.

Patterns of Points in 3D Space

The scatterplot is probably the most effective method for finding unknown patterns in 2D discrete data. When three attributes are given for each data point, one solution is to show it in 3D using depth cues. The attributes are mapped to positions on the x, y, and z axes, respectively. The resulting 3D scatterplot is usually rotated around a vertical axis, exploiting structure-from-motion to reveal its structure (Donoho et al., 1988). This technique can be an alternative to the color- and shape-enhanced scatterplots discussed in Chapters 4 and 5. If needed, color and size can be added to the glyphs of a 3D scatterplot to show even more data attributes. There has been little or no empirical work on the role of depth cues in perceiving structures such as clusters and correlations in 3D. Nevertheless, a number of conclusions can be deduced from our understanding of the way depth cues function.

Only a few depth cues can help with 3D scatterplots. Perspective cues will not help us perceive depth in a 3D scatterplot, because a cloud of small, discrete points has no perspective information. If the points all have a constant and relatively large size, weak depth information will be produced by the size gradient. Similarly, with small points, occlusion will not provide useful depth information, but if the points are larger, some ordinal depth information will be perceivable. If there are a large number of points, cast shadows will not provide information, because it will be impossible to determine the association between a given point and its shadow. Shape-from-shading information will also be missing, because a point has no orientation information. Each point will reflect light equally, no matter where it is placed and no matter where the light source is placed.

It is likely then that the only depth cues in a 3D scatterplot are stereoscopic depth and structure-from-motion. There seems to be little doubt that using both will be advantageous. As with the perception of surfaces, discussed previously, the relative advantages of the different cues will depend on a number of factors. Stereo depth will be optimal for

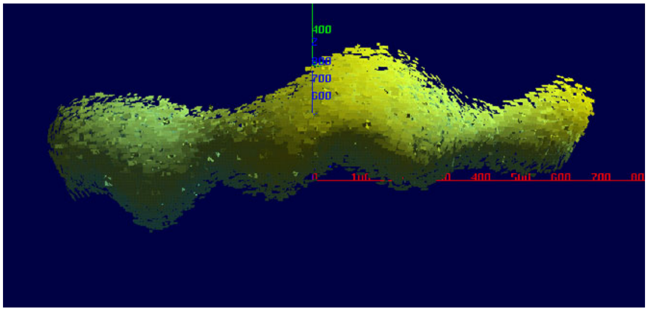


Figure 7.45 A cloud of discrete points is represented by oriented particles. An inverse square law of attraction has been used to determine the point normals. When the cloud is artificially shaded, its shape is revealed (Li, 1997).

fine depth discriminations between points that lie near one another in depth. Structure-from-motion will be more important for points that lie farther apart in depth.

> **[G7.16]** To see depth in a 3D scatterplot, consider generating structure-from-motion cues by rotating or oscillating the point cloud around a vertical axes. Also use stereoscopic viewing if possible.

One of the problems with visualizing clouds of data points is that the overall shape of the cloud cannot easily be seen, even when stereo and motion cues are provided. One way to add extra shape information to a cloud of discrete points is to add shape-from-shading information artificially. It is possible to treat a cloud of data points as though each point were actually a small, flat, oriented object. These flat particles can be artificially oriented, if they lie near the boundary of the cloud, to reveal the shape of the cloud when shading is applied. In this way, perception of the cloud's shape can be considerably enhanced, and shape information can be perceived without additional stereo and motion cues. At the same time, the positions of individual points can be perceived. Figure 7.45 illustrates this.

> **[G7.17]** If it is important to judge the morphology of the outer boundary of a 3D cloud of points, consider employing a statistical approximation method to estimate the local orientation of the cloud surface and use this to shade the individual points.

Perceiving Patterns in 3D Trajectories

A common problem in geospatial visualization is to understand the path of a particle, animal, or vehicle through space. A simple line rendering only provides 2D information and this is therefore unsuitable. Using motion parallax or stereoscopic viewing will help. Also, periodic drop lines to a ground plane can be used. In addition, rendering

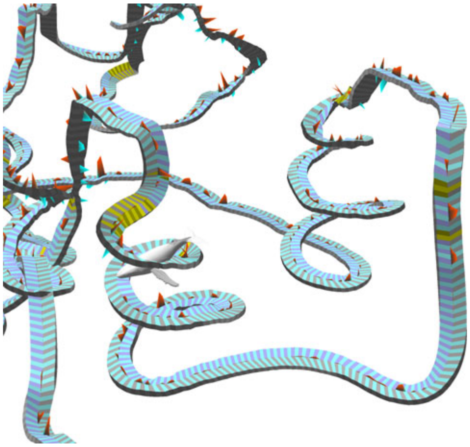


Figure 7.46 The trajectory of a humpback whale bubble-net feeding is shown using an extruded box.

the trajectory as a tube or box adds perspective and shape-from-shading cues, especially if rings are drawn around the tube at periodic intervals. An additional advantage of a box trajectory is that it can also convey roll information. Figure 7.46 shows the trajectory of a humpback whale carrying out a bubble-net feeding maneuver (Ware et al., 2006).

> **[G7.18]** To represent 3D trajectories, consider using shaded tube or box extrusions, with periodic bands to provide orientation cues. Also, apply motion parallax and stereoscopic viewing, if possible.

Judging Relative Positions of Objects in Space

Judging the relative positions of objects is a complex task, performed very differently depending on the overall scale and the context. When very fine depth judgments are made in the near vicinity of the viewer, such as are needed to thread a needle, stereopsis is the strongest single cue. Stereoscopic depth perception is a superacuity and is optimally useful for objects held at about arm's length. For these fine tasks, motion parallax is not very important, as evidenced by the fact that people hold their heads still when threading needles.

In larger environments, stereoscopic depth perception has a minimal role for objects at distances beyond 30 m. Instead, when we are judging the overall layout of objects in a larger environment, known object size, motion parallax, linear perspective, cast shadows, and texture gradients all contribute to our understanding, depending on the exact spatial arrangement.

Gibson (1986) noted that much of size constancy can be explained by a referencing operation with respect to a textured ground plane. The sizes of objects that rest on a uniformly textured ground plane can be obtained by reference to the texture element size. Objects slightly above the ground plane can be related to the ground plane through the shadows they cast. In artificial environments, a very strong artificial reference can be provided by dropping a vertical line to the ground plane.

Because 3D environments can be so diverse and used for so many different purposes, no specific additional guidelines are given here relating to judgments of object position in 3D. The optimal mix is a complex design problem, not something for simple guidelines. All of the depth cues we have been discussing can be applied and should be considered in a design solution.

Judging the Relative Movements of Self within the Environment

When we are navigating through a virtual environment representing an information space, there are a number of frames of reference that may be adopted; for example, an observer may feel she is moving through the environment or that she is stationary and the environment is moving past. In virtual environment systems that are either helmet mounted or monitor based, the user rarely actually physically moves any great distance, because real-world obstacles lie in the way. If self-movement is perceived, it is generally an illusion. Note that this applies only to linear motion, not to rotations; users with helmet-mounted displays can usually turn their heads quite freely.

A sensation of self-movement can be strongly induced when the subject is not moving. This phenomenon, called *vection*, has been studied extensively. When observers are placed inside a large moving visual field—created either by a physical drum or by means of computer graphics within a virtual-reality helmet—they invariably feel that they are moving, even though they are not. A number of visual parameters, discussed below, influence the amount of vection that is perceived.

Field size—In general, the larger the area of the visual field that is moving, the stronger the experience of self-motion (Howard & Heckman, 1989).

Foreground/background—Much stronger vection is perceived if the moving part of the visual field is perceived as background and more distant from the observer than static foreground objects (Howard & Heckman, 1989). In fact, vection can be perceived even with a quite small moving field, if that field is perceived to be relatively distant. The classic example occurs when someone is sitting in a train stopped at a station and the movement of an adjacent train, seen through a window, causes that person to feel that he or she is moving, even though this is not the case.

Frame—Vection effects are considerably increased if there is a static foreground frame between the observer and the moving background (Howard & Childerson, 1994).

Stereo—Stereoscopic depth can determine whether a moving pattern is perceived as background or foreground, and thereby increase or decrease vection (Lowther & Ware, 1996).

In aircraft simulators and other vehicle simulators, the goal is for the user to experience a sense of self-motion, even though the simulator's actual physical motion is relatively small or nonexistent.

One of the unfortunate side effects of this perceived motion is simulator sickness. The symptoms of simulator sickness can appear within minutes of exposure to perceived extreme motion. Kennedy et al. (1989) reported that between 10% and 60% of users of immersive displays experienced some symptoms of simulator sickness. This high incidence may ultimately be a major barrier to the adoption of fully immersive display systems.

Simulator sickness is thought to be caused by conflicting cues from the visual system and the vestibular system of the inner ear. When most of the visual field moves, the brain usually interprets this as a result of self-motion. But, if the observer is in a simulator, no corresponding information comes from the vestibular system. According to this theory, the contradictory information results in nausea. There are ways to ensure that simulator sickness does occur and ways of reducing its effects. Turning the head repeatedly while moving in a simulated virtual vehicle is almost certain to induce nausea (DiZio & Lackner, 1992). This means that a virtual ride should never be designed in which the participant is expected to look from side to side while wearing a helmet-mounted display. Simulator sickness in immersive virtual environments can be mitigated by initially restricting the participant's experience to short periods of exposure, lasting only a few minutes each day. This allows the user to build up a tolerance to the environment, and the periods of exposure can gradually be lengthened (McCauley & Sharkey, 1992).

Selecting and Positioning Objects in 3D

In some interactive 3D visualization environments, users must be able to reach in and manipulate objects, and designers of 3D display systems must make choices about which depth cues to include. In a full-blown virtual-reality system, the usual goal is to include all of the depth cues at the highest fidelity possible, but in practical systems for molecular modeling or 3D computer-aided design, various tradeoffs must be made.

Two of the most important options are whether to use a stereoscopic display and whether to provide motion parallax through perspective coupled to head position. Both require an investment in technology not normally provided with computer workstations. The evidence suggests that, for accurate reaching, having a stereoscopic display is more important than the motion parallax that occurs through the motion of the user's head (and hence eyes) with respect to the objects being selected (Boritz & Booth, 1998; Arsenault & Ware, 2004).

One of the purposes of tracking head (and eye) position is to get a correct perspective view to support eye–hand coordination. A number of researchers have investigated how eye–hand coordination changes when there is a mismatch between feedback from the visual sense and the proprioceptive sense of body position. A typical experiment involves subjects pointing at targets while wearing prisms that displace the visual image relative to the proprioceptive information from their muscles and joints. Subjects adapt rapidly to the prism displacement and point accurately. Work by Rossetti et al. (1993) suggests that there may be two mechanisms at work: a long-term, slow-acting mechanism that is capable of spatially remapping misaligned systems, and a short-term mechanism that is designed to realign the visual and proprioceptive systems within a fraction of a second. These results have been confirmed in studies with fish-tank virtual-reality systems, showing that a large translational offset between the hand position and the object being manipulated with the hand has only a small effect on performance (Ware & Rose, 1999).

If they are large, rotational mismatches between what is seen and what is held may have a much greater negative impact on eye–hand coordination than translational mismatches. Experiments with prisms that invert the visual field have shown that it can take weeks to reach behavior approaching normal performance under this condition, and adaptation may never be complete (Harris, 1965).

In visually guided hand movement, what seems to be most important is feedback about the *relative* positions of the graphical object representing the user's hand (or a probe) and the object itself. The stereoscopic system is exquisitely tuned to depth differences but not to absolute depths. Indeed, one of the main reasons why humans have stereoscopic depth perception is to support visually guided reaching. Research has shown that as long as continuous visual feedback is provided, without excessive lag, people can adjust rapidly to simple changes in the eye–hand relationship (Held et al., 1966).

Getting perfect registration between a user's hand and a virtual object, as shown in Figure 7.47, is very difficult. This suggests that it is better to show both the hand and object virtually, rather than blend real-world and computer graphics imagery, because in this way it is easy to show the relative positions of the hand and object (see Figure 7.47).

[G7.19] Use stereoscopic viewing when visually guided hand movements are critically important. If possible, use a graphical proxy for the user's hand and ensure accurate relative positioning between the hand proxy and the virtual objects to be manipulated.

[G7.20] In 3D environments that support one-to-one mapping between the user's hand and a virtual object, ensure that the relative positions of a hand proxy, such

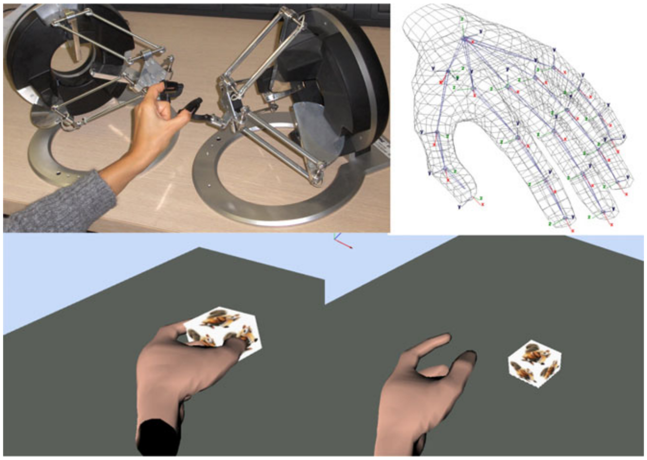


Figure 7.47 If both the hand proxy and the objects are virtual, it is easy to generate the correct relative positions of the hand and object. (*Courtesy of Siena Robotics and Systems Lab. Permission needed http://sirslab.dii.unisi.it/.*)

as a probe, and an object being reached for are correct. Also, minimize rotational mismatch (>30 degrees) between the virtual space and the actual space within which the user's hand is moving.

Actually providing a sense of physical contact with nearby objects is also important in calibrating the proprioceptive system, especially for grasping (Mackenzie & Iberall, 1994). Unfortunately, this component of natural hand–object interaction is proving very difficult to simulate, and, although force feedback devices can provide a sense of contact, they currently have limited capabilities.

Judging the "Up" Direction

In abstract 3D data spaces (for example, molecular models), there is often no sense of an "up" direction, and this can be confusing. In the natural environment, the "up" direction is defined by gravity and sensed by the vestibular system in the inner ear, by the presence of the ground on which we walk, and by oriented objects in our vicinity. Much of the research that has been done on perceived "up" and "down" directions has been done as part of space research, to help us understand how people can best orient themselves in a gravity-free environment. Nemire et al. (1994) showed that linear perspective provides a strong cue in defining objects perceived at the same horizontal level. They showed that a linear grid pattern on the virtual floor and walls of a display strongly influenced what the participants perceived as horizontal; to some extent, this overrode the perception of gravity. Other studies have shown that placing recognizable objects in the scene very strongly influences a person's sense of self-orientation. The presence of recognizable objects with a known normal orientation with respect to gravity, such as a chair or a standing person, can strongly influence which direction is perceived as up (Howard & Childerson, 1994). Both of these findings can easily be adapted to virtual environments.

> **[G7.21]** To define vertical polarity in a 3D data space, provide a clear reference ground plane and place recognizable objects on it that have a characteristic orientation with respect to gravity.

The Aesthetic Impression of 3D Space (Presence)

One of the most nebulous and ill-defined tasks related to 3D space perception is achieving a sense of *presence*. What is it that makes a virtual object or a whole environment seem vividly three dimensional? What is it that makes us feel that we are actually present in an environment? Much of presence has to do with a sense of engagement, and not necessarily with visual information. A reader of a powerfully descriptive novel may visualize (to use the word in its original cognitive sense) himself or herself in a world of the author's imagination—for example, vividly imagining Ahab on the back of the great white whale, Moby-Dick.

Presence might not seem to belong in a task-based classification of spatial information, being usually thought of as an ill-defined aesthetic quality, but in fact a number of practical applications require a sense of presence. For an architect designing a virtual building to present to a client, the feeling of spaciousness and the aesthetic quality of that space may be all-important. In virtual tourism, where the purpose is to give a potential traveler a sensation of what the Brazilian rain forest is really like, presence is also crucial.

A number of studies have used virtual-reality techniques for phobia desensitization. In one study by North et al. (1996), patients who had a fear of open spaces (agoraphobia) were exposed to progressively more challenging virtual open spaces. The technique of progressive desensitization involves taking people closer and closer to the situations that cause them fear. As they overcome their fears at one level of exposure, they can be taken to a slightly more stressful situation. In this way, they can overcome their phobias, one step at a time. The reason for using virtual-reality simulations in phobia desensitization is to provide control over the degree of presence and to reduce the stress level by enabling the patient to exit the stressful environment instantaneously. After treatment in a number of virtual environments, the experimental subjects of North et al. scored lower on a standardized Subjective Units of Discomfort test.

When developing a virtual-reality theme park attraction for Disneyland, Pausch et al. (1996) observed that high frame rate and high level of detail were especially important in creating a sense of presence for users "flying on a magic carpet." Presenting a stereoscopic display did not enhance the experience. Empirical studies have also shown that high-quality structure-from-motion information contributes more to a sense of presence than does stereoscopic display (Arthur et al., 1993). The sense of presence, however, is not a single unified perceptual dimension. Hendrix and Barfield (1996) found stereoscopic viewing to be very important when subjects were asked to rate the extent to which they felt they could reach for and grasp virtual objects, but it did not contribute at all to the sense of the overall realism of the virtual condition. Hendrix and Barfield did find that having a large field of view was important to creating a sense of presence.

[G7.22] To create a vivid sense of presence in a 3D data space, provide a large field of view, smooth motion, and a lot of visual detail.

Conclusion

High-quality, interactive stereoscopic displays are now inexpensive, although even mediocre-quality virtual-reality systems are still expensive. Creating a 3D visualization environment is considerably more difficult than creating a 2D system with similar capabilities. We still lack design rules for 3D environments, and many interaction techniques are competing for adoption. The strongest argument for the ultimate ascendancy of 3D visualization systems, and 3D user interfaces in general, must be that we live in a 3D world and our brains have evolved to recognize and interact within 3D. The 3D design space is richer than the 2D design space, because a 2D space is a part of 3D space. It is always possible to flatten out part of a 3D display and represent it in 2D.

Nevertheless, it also should be cautioned that going from 2D to 3D adds far less visual information than might be supposed. Consider the following simple argument. On a one-dimensional line of a computer display, we can perceive 1000 distinct pixels. On a 2D plane of the same display, we can display $1000 \times 1000 = 1{,}000{,}000$ pixels, but going to a 3D stereoscopic display only increases the number of pixels by a factor of 2, and this does not double the available information because the two images must be highly correlated for us to perceive stereoscopic depth. We may only be able to stereoscopically fuse images that differ by 10%, usually much less. This suggests a small increase in the amount of information through the use of stereo viewing.

Of all the depth cues, motion parallax is the one most likely to enable us to see more information, but only for certain cognitive tasks. In the case of networks, a network several times larger can be perceived with stereo and motion parallax cues, although even here, if interaction with nodes is critical, interactive 2D methods are likely to be superior. The other depth cues, such as occlusion and linear perspective, certainly help us perceive a *coherent* 3D space, but as the study of Cockburn and McKenzie (2001) suggests, we should not automatically assume that 3D provides more readily accessible information. Most of the pattern-perception machinery of the visual system operates in 2D, not in 3D, and for this fundamental reason even when a 3D view is being used it is critical to understand what pattern information appears on the 2D image plane.

Deciding whether or not to use a 3D display must involve deciding whether there are sufficient important subtasks for which 3D is clearly beneficial. The complexity and the consistency of the user interface for the whole application must be weighed in the decision. Even if 3D is better for one or two subtasks, the extra cost involved and the need for nonstandard interfaces for the 3D components may suggest that a 2D solution would be better overall. In terms of overall assessment, the cost of navigation is an essential component, and many 3D navigation methods are considerably slower than 2D alternatives. Even if we can show somewhat more information in 3D, the rate of information access may be too slow. In Chapter 10, we shall resume the discussion of the value of 3D versus 2D displays by considering the various costs of interactively acquiring knowledge.

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CHAPTER EIGHT

Visual Objects and Data Objects

The object metaphor is pervasive in the way we think about information, no matter how abstract. Object-oriented programming is one example; the body politic is another. Object-related concepts are also basic in modern systems design. A modular system is one that has easily understood and easily replaced components. Good modules are plug compatible with one another; they are discrete and separate parts of a system. The concept of a module has a lot in common with the perceptual and cognitive structures that define visual objects. This suggests that visual objects may be an excellent way to represent modular system components. A visual object provides a useful metaphor for encapsulation and cohesiveness, both important concepts in defining modular systems.

In purely visual terms, an object can be thought of as any identifiable, separate, and distinct part of the visual world. Information about visual objects is cognitively stored in a way that ties together critical features, such as oriented edges and patches of color and texture, so that they can be identified, visually tracked, and remembered. Because visual objects cognitively group visual attributes, if we can represent data values as visual features and group these features into visual objects, we will have a very powerful tool for organizing related data.

Two radically different types of theory have been proposed to explain object recognition. The first is image based. It proposes that we recognize an object by matching the visual image with something roughly like a snapshot stored in memory. The second type is structure based. It proposes that objects are analyzed in terms of primitive three-dimensional (3D) forms and the structural interrelationships between them. Both of these models have much to recommend them, and it is entirely plausible that each is

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correct in some form. It is certainly clear that the brain has multiple ways of analyzing visual input. Both models provide interesting insights into how to display data effectively. We begin with the image-based theory of object recognition and examine some evidence supporting it.

Image-Based Object Recognition

The image-based theory is supported by the fact that people have a truly remarkable ability to recognize pictorial images they have seen before. In an arduous experiment, Standing et al. (1970) presented subjects with 2560 pictures at a rate of one every 10 seconds. This was like the family slide show from hell; it took more than 7 hours spread over a 4-day period to show them all. Amazingly, when subsequently tested, subjects were able to distinguish pictures from others not previously seen with better than 90% accuracy.

It is important to make a distinction between *recognition* and *recall*. We have a great ability to recognize information that we have encountered before, as the picture memory experiment of Standing et al. shows. However, if we are asked to reconstruct visual scenes—for example, to recall what happened at a crime scene—our performance is much worse. Recognition is much better than recall. People did not really remember all of those pictures; they were only able to say, tentatively, that they might have seen them.

People can also recognize objects in images that are presented very rapidly. Suppose you asked a group of people "Is there a dog in one of the following pictures?" and then showed them a set of images, rapidly, all in the same place, at a rate of 10 per second. Remarkably, they will be able to detect the presence, or absence, of a dog, somewhere in the sequence of images most of the time. This experimental technique is called *rapid serial visual presentation* (RSVP). Experiments have shown that the maximum rate for the ability to detect common objects in images is about 10 images per second (Potter & Levy, 1969; Potter, 1976). We should interpret this result cautiously. Although interesting, it does not mean that people processed more than a small amount of information from each image.

A related phenomenon is *attentional blink*. If, in a series of images, a second dog were to appear in an image within 350 ms of the first, people do not notice it (or anything else). This moment of blindness is the attentional blink (Coltheart, 1999). It is conjectured that the brain is still processing the first dog, even though the image is gone, and this prohibits the identification of other objects in the sequence.

More support for image-based theories comes from studies showing that three-dimensional objects are recognized most readily if they are encountered from the same view direction as when they were initially seen. Johnson (2001) studied subjects' abilities to recognize bent pipe structures. Subjects performed well if the same viewing direction was used in the initial viewing and in the test phase. They performed poorly if a different view direction was used in the test phase, but they were also quite good at identification from exactly the opposite view direction. Johnson attributed this unexpected finding to the importance of silhouette information. Silhouettes would have been similar, although flipped left-to-right from the initial view.

Although most objects can easily be recognized independent of the size of the image on the retina, image size does have some effect. Figure 8.1 illustrates this. When the picture is seen from a distance, the image of the Mona Lisa face dominates; when it is viewed up close, smaller objects become dominant: A gremlin, a bird, and a claw emerge. Experimental work by Biederman and Cooper (1992) suggests that the optimal size for recognizing a visual object is about 4 to 6 degrees of visual angle. This gives a useful rule of thumb for the optimal size for rapid presentation of visual images so that we can best see the visual patterns contained in them.

[G8.1] For optimal identification, make important patterns and complex objects so that they have a size of approximately 4 to 6 degrees of visual angle. This is not a rigid requirement, as there is only a gradual falloff in skill as we depart from the optimal.

Figure 8.1 When the image is viewed from a distance, the face dominates, but when looked at from 30 cm the gremlin hiding in the shadows of the mouth and nose emerges. At this distance, the gremlin has a visual angle of about 4 degrees, optimal for seeing a pattern. (*Adapted from the work of the Tel Aviv artist Victor Molev.*)

Priming

If you identify something, even if it is a fleeting meaningless encounter, you will identify it faster if you see it again in the near future (Bartram, 1974). This effect is called *priming*. Most studies of priming involve intervals between the two events of minutes or hours, but Cave and Squire (1992) showed priming effects for picture naming that lasted for weeks.

Priming effects can occur even if information is not consciously perceived, and because of this priming is sometimes called *implicit memory*. Bar and Biederman (1998) exposed pictorial images to subjects so briefly that it was impossible for them to identify the objects. They followed the brief image exposure with what is called a *visual mask*, a random pattern shown immediately after the target stimulus to remove the target from the visual iconic store (a short-term buffer that holds the visual image for a fraction of a second), and they rigorously tested to show that subjects performed at chance levels when reporting what they had seen. Nevertheless, 15 minutes later, this unperceived exposure substantially increased the chance of recognition. Although the information was not consciously perceived, exposure to the particular combination of image features apparently primed the visual system to make subsequent recognition easier. They found that the priming effect decreased substantially if the imagery was displaced sideways. They concluded that the mechanism of priming is highly image dependent and not based on high-level semantic information.

Lawson et al. (1994) devised a series of experiments in which subjects were required to identify a specified object in a series of briefly presented pictures. Recognition was much easier if subjects had been primed by *visually similar* images that were not representations of semantically related objects. They argued that this should not be the case if objects are recognized on the basis of a high-level, 3D structural model of the kind that we will discuss later in this chapter; only image-based storage can account for their results. All of this adds support to the image-based theory of object recognition, because the effects are based on two-dimensional (2D) image information.

Also adding support to the multiple-view, image-based theory of object recognition is neurophysiological evidence from recordings of single cells in the inferotemporal cortexes of monkeys. Perrett et al. (1991) discovered cells that respond preferentially to particular views of faces. Figure 8.2 shows some of their results. One cell (or cell assembly) responds best to a three-quarter view of a face; another to profiles, either left or right; still another to a view of a head from any angle. We can imagine a kind of hierarchical structure, with the cell assemblies that respond to particular views feeding into higher level cell assemblies that respond to any view of the object.

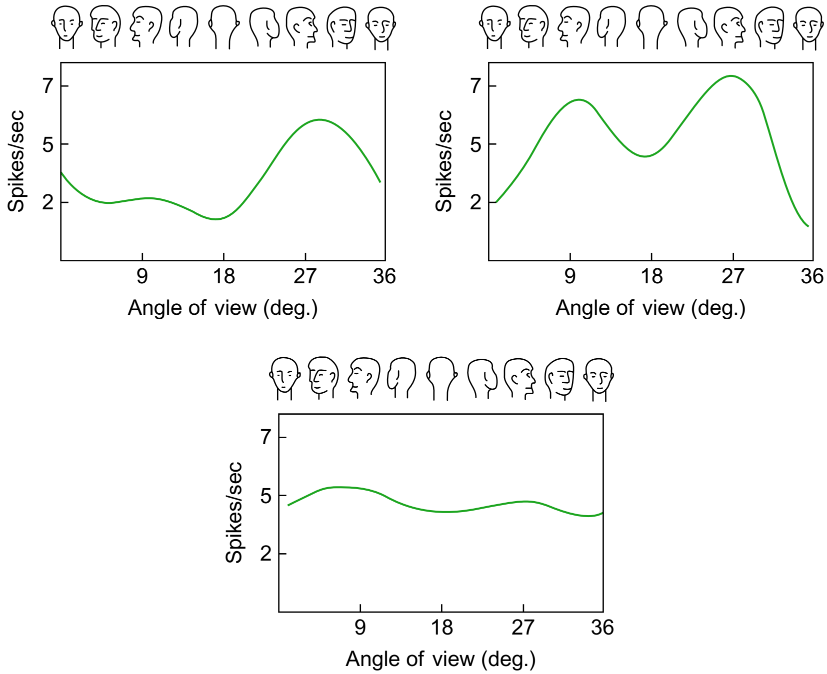


Figure 8.2 The responses of three neurons in the temporal cortex of a monkey to faces in different orientations. At the top left is a cell most sensitive to a right profile; the right cell responds well to either profile; the cell at the bottom responds to a head irrespective of orientation.

Searching an Image Database

Presenting images rapidly in sequence (RSVP) may be a useful way to allow users to scan picture databases (Wittenburg et al., 1998; de Bruijn et al., 2000). The fact that people can search rapidly for an image in a sequence of up to 10 pictures per second suggests that presenting images using RSVP may be efficient. Contrast this with the usual method of presenting image collections in a regular grid of small thumbnail images. If it is necessary to make an eye movement to fixate each thumbnail image, it will not be possible to scan more than three to four images per second. Even though RSVP seems promising, there are a number of design problems that must be solved in building a practical interface. Once a likely candidate image is identified as being present in an RSVP sequence, the particular image must be extracted from the set. By the time a user responds with a mouse click several images will have passed, more if the user is not poised to press the stop button. Thus, either controls must be added for backing up through the sequence, or part of the sequence must be fanned out in a conventional thumbnail array to confirm that candidate's presence and study it further (Wittenburg et al., 1998; Spence, 2002).

Rapid serial presentation may also provide a way of searching video content by viewing a rapidly presented sequence of selected frames (Tse et al., 1998). Wildemuth et al. (2003) suggested that a speed up of 64× faster than the original video may be optimal in allowing viewers to get the gist of what is occurring. Video data compressed in this way might make it possible to review a day's worth of video in a few minutes.

Life Logging

It is becoming possible to have a personal memory data bank containing video and audio data collected during every waking moment through the course of a person's lifetime. This can be achieved with an unobtrusive miniature camera, perhaps embedded in a pair of eyeglasses, and, assuming continuing progress in solid-state storage, the data can be stored in a device weighing a few ounces and costing a few hundred dollars (Gemmel et al., 2006). The implications of such *life logging* devices seem profound at first encounter; they appear to represent the ultimate memory aid—the user need never forget anything.

A key issue, though, is the interface to the stored data. If we want to recall a meeting we know happened sometime in 2004 we clearly cannot replay the entire year's worth of data to find the event, even very fast. But the most serious problem for the life logging concept is that seeing a video replay is not at all the same as remembering. A replay of some forgotten event, such as a meeting, will be more akin to a re-experience, one that occurs without the context of the goals of the person involved, even if it is oneself. When people review their own videos, they do not spontaneously remember what happened; instead, they must mentally reconstruct it (Sellen et al., 2007). A meaningful reconstruction of a particular meeting may require a review of videos of other activities for weeks prior to the event, together with relevant documents and e-mail communications between the participants. The result is that a reconstruction of a single meeting might take days of work if a well-designed interface to the data is available.

Such arguments have led researchers to suggest that the main value of life logging is to jog the memory of the participant rather than being a substitute for memory. Accordingly, a study by Sellen et al. (2007) investigated the value of video imagery in helping people recall personal events using their *SenseCam* system. They found that a few days later SenseCam imagery roughly doubled the number of events that could be recalled, from two to four, for a particular half-day interval.

Another SenseCam application that has been explored is its use as an aid for the memory impaired. A trial was conducted in collaboration with a woman who had damage to the hippocampus area, a part of the brain that is involved in the ability to form long-term memories. In a comparison between careful note taking, the use of SenseCam video, and no aids, the SenseCam approach proved most effective, but the method involved the woman reviewing recent videos with her husband to construct meaning from them. So, again, it was not the video itself that provided the memory; rather, it was the video being used as a tool in the active construction of memories.

Overall, the research results suggest that video imagery can indeed help to support memory to some extent, but it does not provide anything close to perfect recall.

Structure-Based Object Recognition

Image-based theories of object recognition imply a rather superficial level of analysis of visual objects, but there is evidence that a much deeper kind of structural analysis must also occur. Figure 8.3 shows two novel objects, probably never seen by the reader before. Yet, despite the fact that the images in Figure 8.3(a) and (c) are very different from one another, they can be rapidly recognized as representations of the same object. No image-based theory can account for this result; it can only be based on a structural analysis of the relationships of the component parts.

Geon Theory

Figure 8.4 provides a somewhat simplified overview of a neural network model of structural object perception, developed by Hummel and Biederman (1992). This theory proposes a hierarchical set of processing stages leading to object recognition. Visual information is decomposed first into edges, then into component axes, oriented blobs, and vertices. At the next layer, 3D primitives such as cones, cylinders, and boxes, called *geons*, are identified. A selection of geons is illustrated in Figure 8.5(a). Next, the structure is extracted that specifies how the geon components interconnect; for example, in a human figure, the arm cylinder is attached near the top of the torso box. Finally, object recognition is achieved.

Silhouettes

Silhouettes appear to be especially important in determining how we perceive the structure of objects. The fact that simplified line drawings are often silhouettes may, in part, account for our ability to interpret them. At some level of perceptual processing, the silhouette boundaries of objects and the simplified line drawings of those objects excite

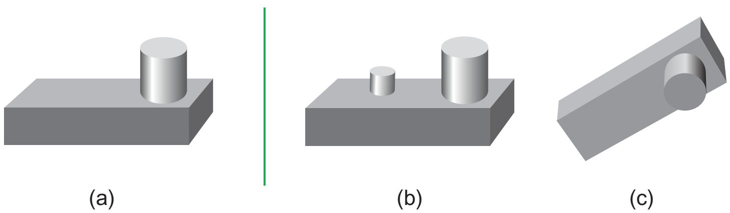


Figure 8.3 The object shown in (a) seems most similar to the object shown in (c), despite the fact that the *images* of (a) and (b) are most similar.

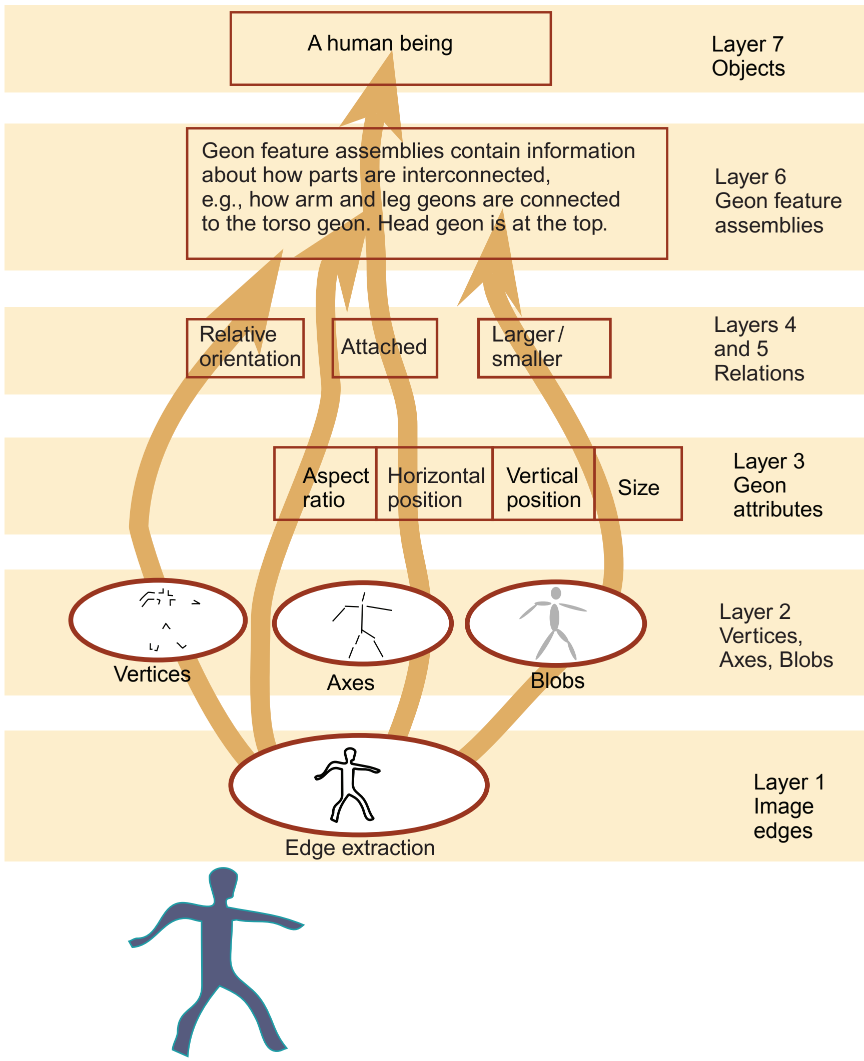


Figure 8.4 A simplified view of Hummel and Biederman's (1992) neural network model of form perception.

the same neural contour extraction mechanisms. Halverston (1992) noted that modern children tend to draw objects on the basis of the most salient silhouettes, as did early cave artists. Many objects have particular silhouettes that are easily recognizable—think of a teapot, a shoe, a church, a person, or a violin. These canonical silhouettes are based on a particular view of an object, often from a point at right angles to a major plane of symmetry. Figure 8.6 illustrates canonical views of a teapot and a person.

David Marr suggested ways in which the brain might use silhouette information to extract the structures of objects (Marr, 1982). He argued that "buried deep in our

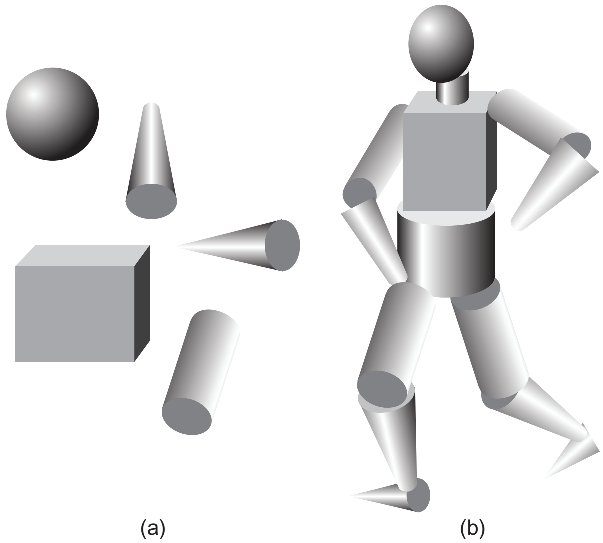


Figure 8.5 According to Biederman's geon theory, the visual system interprets 3D objects by identifying 3D component parts called *geons*. (a) A sample of geons. (b) A human figure constructed from geons.

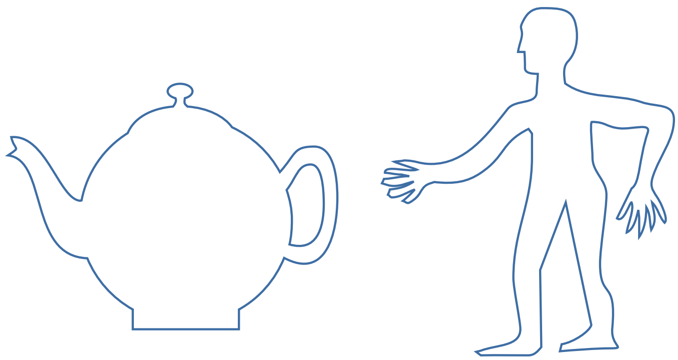


Figure 8.6 Many objects have canonical silhouettes, defined by the viewpoints from which they are most easily recognized. In the case of the man, the overall posture is unnatural, but the component parts—hands, feet, head, etc.—are all given in canonical views.

perceptual machinery" are mechanisms that contain constraints determining how silhouette information is interpreted.

Three rules are embedded in this perceptual machinery:

1. Each line of sight making up a silhouette grazes the surface exactly once. The set of such points is the contour generator. The idea of the contour generator is illustrated in Figure 8.7.

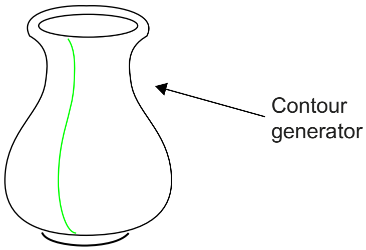


Figure 8.7 According to Marr, the perceptual system makes assumptions that occluding contours are smoothly connected and lie in the same plane. (*Adapted from Marr (1982).*)

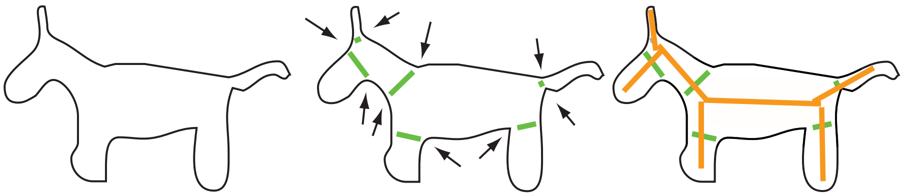


Figure 8.8 Concave sections of the silhouette define subparts of the object and are used in the construction of a structural skeleton. (*Redrawn from Marr & Nishihara (1978).*)

2. Nearby points on the contour of an image arise from nearby points on the contour generator of the viewed object.
3. All the points on the contour generator lie on a single plane.

Under Marr's default assumptions, contour information is used in segmenting an image into its component solids. Marr and Nishihara (1978) suggested that concave sections of the silhouette contour are critical in defining the ways in which different solid parts are perceptually defined. Figure 8.8 illustrates a crudely drawn animal that we nevertheless readily segment into head, body, neck, legs, and so on. The most important features for this segmentation are concavities in the silhouette. Marr and Nishihara also proposed that the axes of the parts become cognitively connected to form a structural skeleton, so the object description consists of component parts and a description of how they are connected.

One of the consequences of structural theories of perception is that certain simplified views should be easier to read. There are practical advantages to this; for example, a clear diagram may sometimes be more effective than a photograph. This is exactly what Ryan and Schwartz (1956) showed when they found that a hand could be perceived more rapidly in the form of a simplified line drawing than in the form of a photograph (see Figure 8.9), but this result should not be overgeneralized. Other studies have shown that time is required for detailed information to be perceived (Price & Humphreys, 1989; Venturino & Gagnon, 1992). Simplified line drawings may be most appropriate only when rapid responses are required.

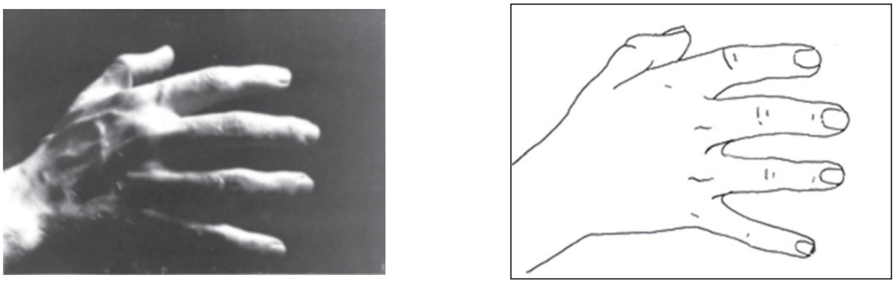


Figure 8.9 A photograph and a simplified line drawing of a hand. Ryan and Schwartz (1956) showed that a cartoon drawing was recognized more rapidly than a photograph.

Although image-based theories and structure-based theories of object recognition are usually presented as alternatives, it may be that both kinds of processes occur. If geons are extracted based on concavities in the silhouette, certain views of a complex object will be much easier to recognize. Further, it may well be that viewpoint-dependent aspects of the visual image are stored in addition to the 3D structure of the object. Indeed, it seems likely that the brain is capable of storing many kinds of information about an object or scene if they have some usefulness. The implication is that, even though 3D objects in a diagram may be more effective in some cases, care should be taken to provide a good 2D layout. Both image-based cues and structural cues should be clearly presented.

The Object Display and Object-Based Diagrams

Wickens (1992) is primarily responsible for the concept of an object display as a graphical device employing a "single contoured object" to integrate a large number of separate variables. Wickens theorized that mapping many data variables onto a single object will guarantee that these variables are processed together, in parallel. This approach, he claimed, has two distinct advantages. The first is that the display can reduce visual clutter by integrating the variables into a single visual object. The second is that the object display makes it easier for an operator to integrate multiple sources of information.

Generally, object displays will be most effective when the components of the objects have a natural or metaphorical relationship to the data being represented. Figure 8.10 shows an object display developed for anesthesiologists working in operating theaters. It is the responsibility of anesthesiologists to monitor the output from a large number of sensors attached to a patient and from the reading to infer the state of the patient, especially relating to the delivery of oxygen to the brain through the cardiovascular system. George Blike and his coworkers developed a display that maps these instrument readings to a set of complex glyphs as illustrated in the figure (Blike et al., 1999). The central glyph represents the heart and this incorporates four different measurements. The height of the glyph represents the volume pumped by a single heart-beat, and its width represents the heart rate (number of beats per minute). The glyph size is an emergent

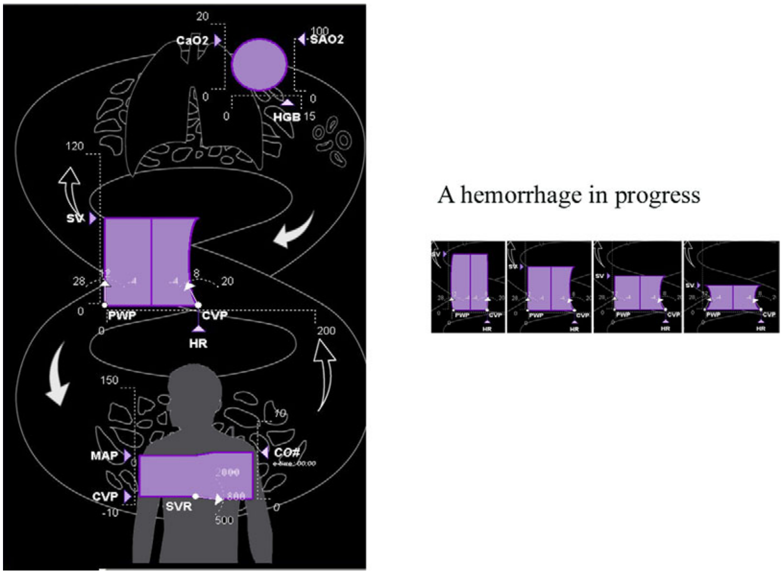


Figure 8.10 A geon diagram design for use by anesthesiologists (Blike et al., 1999). (© *Draeger Medical Systems, Inc. All rights reserved. Not to be reproduced without written permission.*)

property showing overall heart throughput. The bowing or bulging of the sides of the heart object is produced from two cleverly transformed measurements, the pulmonary wedge pressure (PWP) and the central venous pressure (CVP), representing the pressure in the left- and right-hand sides of the heart, respectively. These control the degree of convexity or concavity on each side of the glyph in such a way that a concave shape is the result of too low pressure and a convex shape is the result of too high pressure. This provides an intuitive visual metaphor for these variables. The display enables an anesthesiologist to rapidly diagnose problems such as an embolism (blockage) or hemorrhage, and the laterality of the bulge or concavity indicate where they are occurring. In an evaluation study comparing this display with a more conventional display, errors were reduced by 66%.

In the Blike design, the object display has a number of clear advantages. It can reduce accidental misreadings of data values. Mistakes are less likely because components act as their own descriptive icons. In addition, the structural architecture of the system and the connections between system components are always visible, and this may help in diagnosing the causes and effects of problems.

The disadvantage of object displays is that they lack generality; an object display must be custom designed for each specific application, which means that they are only appropriate when a great deal of effort can be devoted to a careful design. Object displays should be validated with a user population to ensure that the data representation is clear and properly interpreted. This requires far more effort than displaying data as a table of numbers or a simple bar chart.

[G8.2] Consider using an object display where standardized sets of data must be repeatedly analyzed and where the data can be mapped to semantically meaningful objects.

The general properties of an effective object display are summarized in the following guidelines.

[G8.3] Design object displays in such a way that numbers are tied to recognizable visual objects representing system components.

[G8.4] Design object display layouts using connecting elements that clearly indicate the physical connections between components of a system.

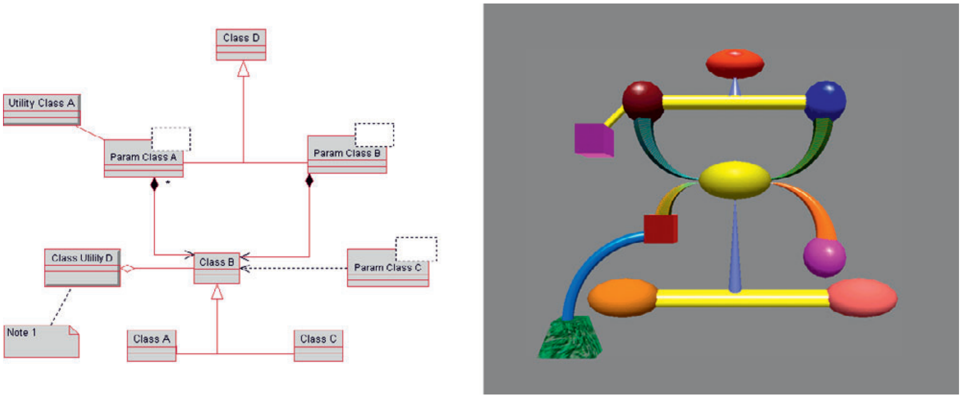
[G8.5] Design object display glyphs to have emergent properties revealing the effect of important interactions between variables.

[G8.6] Design object display glyphs to become more salient when critical values are reached in the data.

The Geon Diagram

Biederman's geon theory, outlined earlier, can be applied directly to object display design. If cylinders and cones are indeed perceptual primitives, it makes sense to construct diagrams using these geon elements. This should make the diagrams easy to interpret if a good mapping can be found from the data to a geon structure. The geon diagram concept is illustrated in Figure 8.11(b). Geons are used to represent the major components of a compound data object, whereas the architecture of the data object is represented by the structural skeleton linking the geons. The size of a geon becomes a natural metaphor for the relative importance of a data entity, or its complexity or relative value. The strength of the connections between the components is given by the neck-like linking structures. Additional attributes of entities and relationships can be coded by coloring and texturing.

We evaluated the geon diagram concept in a comparison with Unified Modeling Language (UML) diagrams (Irani et al., 2001). UML is a widely used, standardized diagramming notation for representing complex systems. Equivalent diagrams were constructed by matching geon elements to UML elements, as shown in Figure 8.11(a).



(a) (b)

Figure 8.11 (a) Unified Modeling Language (UML) diagram. (b) Geon diagram constructed using a subset of Biederman's geon primitives. Both diagrams show the same set of entities and relationships.

We found that when the task involved rapid identification of substructures in a larger diagram, participants performed both faster and with only half the errors using the geon diagrams. Another experiment showed that geon diagrams were easier to remember.

In Biederman's theory, surface properties of geons, such as their colors and textures, are secondary characteristics. This makes it natural to use the surface color and texture of the geon to represent data attributes of a data object. The important mappings between data and a geon diagram are as follows.

Although the geon diagram is a 3D representation, there are reasons to pay special attention to the way it is laid out in 2D in the x, y plane. As discussed earlier, some silhouettes are especially effective in allowing the visual system to extract object structure. A commonsense design rule is to lay out structural components principally on a single plane. A diagramming method resembling the bas-relief stone carvings common in classical Rome and Greece may be optimal. Such carvings contain careful 3D modeling of the component objects, combined with only limited depth and a mainly planar layout.

[G8.7] Consider representing system components using geons—simple 3D shaded objects such as spheres, cylinders, cones, and boxes.

[G8.8] Consider using the color and surface texture of geons to represent secondary attributes of represented entities.

[G8.9] Consider using a geon-based diagram in instances where the diagram is relatively simple, fewer than 30 components, and where entities and relationships must be shown.

[G8.10] Consider representing relationships between components by means of joints between objects. Tubes can be used to express certain types of relations. A small geon attached to a larger geon can show that it is a component part.

[G8.11] Consider using geon shapes to represent the primary attribute of represented entities.

[G8.12] When creating 3D diagrams, lay out system components as much as possible in a 2D plane orthogonal to the line of sight. Be sure that connections between diagram components are clearly visible.

Abstract semantics may be expressible, in a natural way, through the way geons are interconnected. In the everyday environment there is meaning to the relative positioning of objects that is understood at a deep, possibly innate level. Because of gravity, *above* is different from *below*. If one object is *inside* another transparent object, it is perceived either as *contained* by that other object or as a *part of* it. Irani et al. (2001) suggested that the semantics inherent in the different kinds of relationships of real-world objects might be applied to diagramming abstract concepts. Based on this idea, the researchers developed a set of graphical representations of abstract concepts. Some of the more successful of these mappings are illustrated in Figure 8.12 and listed as follows. Only some of these are given formal status as guidelines.

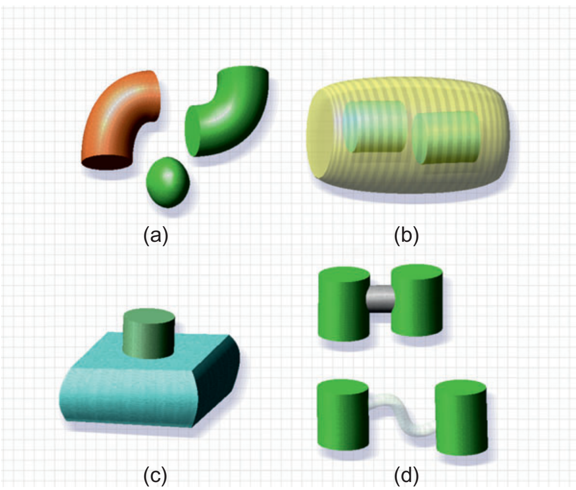


Figure 8.12 Certain spatial relationships between objects can readily represent abstract concepts. (a) That objects belong to the same class is better shown by shape than by color. (b) A part-of relationship. (c) A dependency relationship. (d) Strong and weak relationships.

- Sometimes we wish to show different instances of the same generic object. Geon theory predicts that having the same shape should be the best way of doing this. Geon shape is dominant over color, which is a secondary attribute. Thus, the elbow shapes in Figure 8.12(a) are seen as two instances of the same object, whereas the two green objects are not.
- Having an object inside another transparent object is a natural representation of a part-of relationship. The inside objects seem part of the outside object, as seen in Figure 8.12(b).

[G8.13] When creating 3D diagrams, consider placing an object inside a second transparent object to express a part-of relationship.

- One object above and touching another, as shown in Figure 8.12(c), is easily understood as representing a dependency relationship.
- A thick bar between two objects is a natural representation of a strong relationship between two objects; a thinner, transparent bar represents a weak relationship. See Figure 8.12(d).

[G8.14] When creating diagrams showing entities and relationships, use properties such as size and thickness to represent the strength of the relationship between entities.

Faces

Faces are special objects in human perception. Infants learn about faces faster than they learn about other objects. We are born with visual systems primed to learn to recognize important humans, especially our own mothers (Bushnell et al., 1989; Morton & Johnson, 1991; Bruce & Young, 1998). A specific area of our brains, the right middle fusiform gyrus, is critically important in face perception (Puce et al., 1995; Kanwisher et al., 1997; Kanwisher et al., 1999). This area is also useful for recognizing other complex objects, such as automobiles. Faces have an obvious importance in communication; we use facial expressions to communicate our emotion and degree of interest. Cross-cultural studies by Paul Ekman and coworkers strongly suggest that certain human expressions are universal communication signals, correctly interpreted across cultures and social groups (Ekman & Friesen, 1975; Ekman, 2003). Ekman identified six universal expressions: anger, disgust, fear, happiness, sadness, and surprise. These are illustrated in Figure 8.13, along with determination and elation (a variation on happiness).

The motion of facial features is also important in conveying emotion. Animated images are necessary to convey a full range of nuanced emotion; it is especially important to show motion of the eyebrows (Basilli, 1978; Sadr et al., 2003). Both static and dynamic facial expressions are produced by the contractions of facial muscles, and the *facial action coding system* (FACS) is a widely applied method of

Figure 8.13 Happiness, elation, anger, sadness, disgust, determination, fear, and surprise.

measuring and defining groups of facial muscles and their effect on facial expression (Ekman et al., 1988).

The eyebrows and mouth are particularly significant in signaling emotions, but the shape of the eyes is also important. There is evidence that false smiles can be distinguished from true smiles from the particular expression around the eyes that occurs with the contraction of a muscle that orbits the eye (Ekman et al., 1988; Ekman, 2003). This muscle contracts with true smiles but not with false ones. According to Ekman (2003) it is difficult, if not impossible, to control this voluntarily and thus fake a "true" smile.

The main application of FACS theory in computer displays has been in the creation of computer avatars that convey human emotion (Kalra et al., 1993; Ruttkay et al., 2003). Appropriate emotional expression may help make a virtual salesperson more convincing. In computer-aided instruction, the expression on a human face could reward or discourage. The little symbols called *emoticons*, such as Θ and Λ, commonly used in text messaging take advantage of the ease with which we recognize emotions even when expressed using the most rudimentary graphics.

> **[G8.15]** For perceptually efficient and compact expressions of human emotion, consider using small glyphs representing simplified faces. These are likely to be especially effective in conveying the basic emotions of anger, disgust, fear, happiness, sadness, and surprise.

Among the earlier examples of object displays are Chernoff faces, named after their inventor, Herman Chernoff (1973). In his technique, a simplified image of a human face is used as a display. Examples are shown in Figure 8.14. To turn a face into a display, data variables are mapped to different facial features, such as the length of the

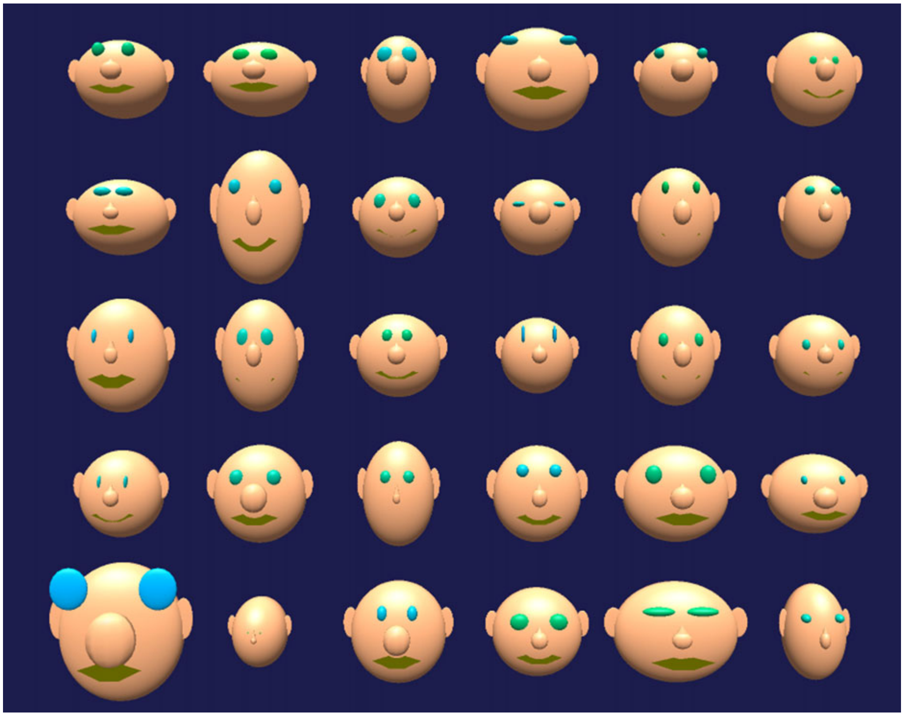


Figure 8.14 Chernoff faces. Different data variables are mapped to the sizes and shapes of different facial features—a bad idea because of unpredictable effects from emergent expressions. (*From dheise@andrews.edu. Permission needed.*)

nose, the curvature of the mouth, the size of the eye, the shape of the head, etc. Jacob et al. (1976) carried out a classification task using a series of displays that were progressively more objectlike. The displays included Chernoff faces, tables, star plots, and the whisker plots described in Chapter 5. They found that more objectlike displays, including Chernoff face plots, enabled faster, more accurate classification.

Despite their initial promise, Chernoff faces have not generally been adopted in practical visualization applications. The likely reason for this is the idiosyncratic nature of the method. When data is mapped to faces, many kinds of perceptual interactions can occur. Sometimes the combination of variables will result in a particular stereotypical face, perhaps a happy face or a sad face, and this will be identified more readily. In addition, there are undoubtedly great differences in our sensitivity to the different features. We may be more sensitive to the curvature of the mouth than to the height of the eyebrows, for example. This means that the perceptual space of Chernoff faces is likely to be extremely nonlinear. In addition, there are almost certainly many uncharted interactions between facial features, and these are likely to vary from one viewer to another, leading to large distortions in the way the data is perceived.

Coding Words and Images

Bertin, in his seminal work, *Semiology of Graphics* (1983), distinguished two distinct sign systems. One cluster of sign systems is associated with auditory information processing and includes mathematical symbols, natural language, and music. The second cluster is based on visual information processing and includes graphics, together with abstract and figurative imagery. More recently, the dual coding of Paivio (1987) proposed that there are fundamentally two different types of information stored in distinct working memory and long-term memory systems; he called them *imagens* and *logogens*. Roughly speaking, imagens denote the mental representation of visual information, whereas logogens denote the mental representation of language information. This duality of systems is called *dual coding theory*.

Visual imagens consist of objects, natural groupings of objects, and whole parts of objects (for example, an arm), together with spatial information about the way they are laid out in a particular environment, such as a room. Logogens store basic information pertaining to language, although not the sounds of the words. Logogens are processed by a set of functional subsystems that provide support for reading and writing, understanding and producing speech, and logical thought. Logogens need not necessarily be tied to speech, but they are associated with non-visual language. In the profoundly deaf the same language subsystems exist and are used in the reading and production of Braille and sign language.

The architecture of dual coding theory is sketched in Figure 8.15. Visual–spatial information enters through the visual system and is fed into association structures in the nonverbal imagen system. Visual text is processed visually at first, but the information is rapidly transferred into the nonvisual association structures of logogens. Acoustic verbal stimuli are processed primarily through the auditory system and then fed into

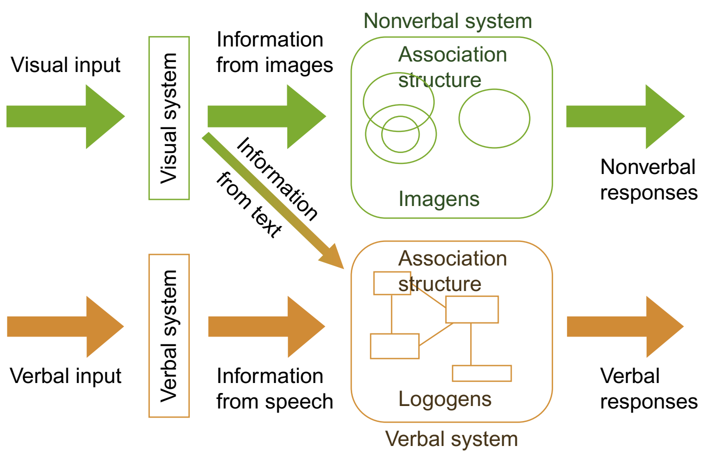


Figure 8.15 Dual coding theory.

the logogen system. Logogens and imagens, although based on separate subsystems, can be strongly interlinked; for example, the word *cat* and language-based concepts related to cats will be linked to visual information related to the appearance of cats and their environment.

Mental Images

Much of dual coding theory is uncontroversial. It has been known for decades that there are different neural processing centers for verbal information and visual information. Examples of purely verbal processing brain regions are Broca's area, which is part of the frontal cortex that when damaged results in an inability to speak intelligibly, and Wernicke's area, which results in an inability to comprehend speech when damaged.

It is the idea that we can "think" visually that is relatively recent. One line of evidence comes from mental imaging. When people are asked to compare the size of a lightbulb with the size of a tennis ball, or the green of a pea with the green of a pine tree, most claim that they use *mental images* of these objects to carry out the task (Kosslyn, 1994). Other studies by Kosslyn and his coworkers show that people treat objects in mental images as if they have real sizes and locations in space. Recently, positron emission tomography (PET) has been used to reveal which parts of the brain are active during specific tasks. This shows that when people are asked to perform tasks involving mental imaging the visual processing centers in the brain are activated. When they mentally change the size and position of an imagined object, different visual areas of the brain are activated (Kosslyn et al., 1993). In addition, if visual processing centers in the brain are damaged, mental imaging ability is disrupted (Farah et al., 1992). It would seem that when we see a cow and when we mentally visualize a cow, the same neural pathways are excited, at least in part. Indeed, modern visual memory theory takes the position that visual object processing and visual object recognition are part of the same process. To some extent, the visual memory traces of objects and scenes are stored as part of the processing mechanism; thus, it is not necessary for an object to be fully processed for recognition to take place (Beardsley, 1997). This can account for the great superiority of recognition over recall. We can easily recognize that we have seen something before, but reproducing it in a drawing or with a verbal description is much more difficult.

This implies that the simple dual coding theory illustrated in Figure 8.15 is misleading in one important respect. The diagram implies that memories for visual inputs are stored *after* processing through the visual system; however, image memory is not a separate storage bin but an integral part of the perceptual system. Visual images are analyzed on their way through the system and visual memories are activated by the incoming information as they simultaneously shape it. There is no separate store; memory is distributed through the brain at every level of processing.

Labels and Concepts

Much of what we perceive when we "see" an object is not out there in the world, but stored in our memories. We perceive objects as tables, chairs, trees, flowers, cups, books, or as one of the thousands of other things we know about. As part of perception, objects are automatically labeled, and our knowledge of the characteristics, uses, and relationships to other objects is brought to a state of readiness in mind. Even an unknown amorphous blob is seen as *like* other objects of a similar size and smoothness—its material properties are automatically inferred from its texture and color, and its potential for manipulation is automatically assessed.

It takes learning and prior experience to develop high-level object concepts, and their characteristics are necessarily somewhat idiosyncratic. A musician will see a violin in a very different way than a nonmusician who hates classical music. In each case, the violin will be seen to have a very different set of affordances and what is perceived will be colored by this. Despite these differences, human communication depends on socially agreed-upon labels for objects, classes of objects, and concepts within a community, and the perception of the more basic characteristics of common objects will be similar for most individuals.

Object Categorization

Categorization is the abstraction of things and ideas into groups and most if not all categories have verbal labels. The words *cheese*, *tree*, *plant*, *company*, and *bacteria* are all category labels. Virtually all of the things we see and think of as objects are classified automatically in the brain within 100 ms of our seeing them. When we see a spoon, not just its shape is registered, but the verbal label also becomes activated. A large array of concepts relating to culinary activity and eating may become primed and brought to a state of readiness.

Objects that we know well combine clusters of attributes that are visual with clusters of attributes that are verbally related concepts. They may also have properties that awaken activities in our movement control systems, in the case of things that we may pick up and manipulate or use as tools. Kahneman et al. (1992) named this collection of visual and nonvisual properties an *object file* (see Figure 8.16).

Even objects that are unfamiliar can be categorized by their utility. A fist-sized chunk of any material may be used as a projectile, as potential building material, or, if it is hard, as a tool.

Our modern understanding of how the human brain categorizes objects began with the pioneering research of Eleanor Rosch (1973, 1975). Prior to this, from the time of Aristotle, object classification had been treated as if the brain did a formal logical analysis of sensory data. This approach leads to a world in which things belong to categories with sharp boundaries. Either something is a fruit, or it is not. Rosch's work showed that the way we actually perceive objects is much more flexible. People

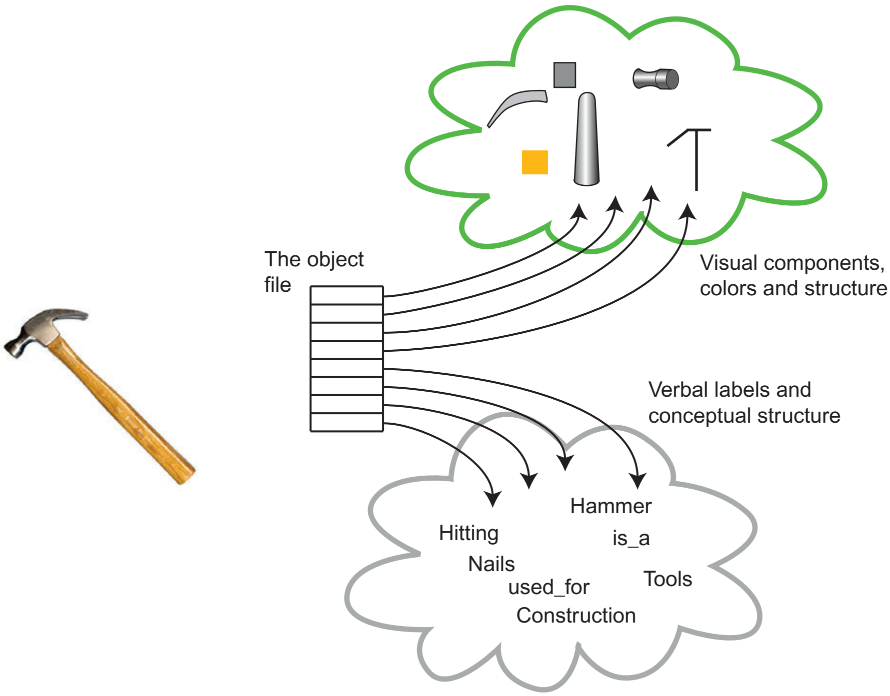


Figure 8.16 The object file is a proposed cognitive mechanism that links multiple attributes of an object. These attributes can be both visual and nonvisual.

perceive apples and oranges to definitively be fruits, but they are much less certain about cucumbers and tomatoes.

Rosch discovered that there are certain categories she called *basic level*, with other categories above and below. The concept of *dog* is a basic-level category, with *animals* as a superordinate category and particular breeds as subordinate categories. Basic-level categories are the most commonly used broad categories and are learned first by infants. People are more likely to categorize a particular animal, such as pet canine, as a dog than as members of the higher level category of animal. Rosch defined basic-level categories in terms of three criteria: *They have similar shape*; this is obviously true of dogs, which are much more mutually similar than, say, the category of animals. *They have similar motor interactions*; that is, we tend to do the same things with members of a particular class. *They have similar nonvisual attributes*, which refers to all the nonvisual properties we learn to be associated with objects, including the materials they are made from and their likely associations with other objects. Because of the visual similarity of basic-level categories, Rosch observed that usually a single drawing can be used to represent the entire class. Such drawings are also classified with the shortest reaction times.

Later work by Jolicoeur et al. (1984) added refinements to Rosch's work. He and his co-workers found that certain category members are identified faster than others even though they are at the same level of the hierarchy. For example, a medium-sized canine with neither especially long or short legs will be categorized as a dog faster than a dachshund.

Canonical Views and Object Recognition

Palmer et al. (1981) showed that not all views of an object are equally easy to recognize. They found that many different objects have something like a *canonical view* from which they are most easily identified. From this and other evidence, a theory of object recognition has been developed, proposing that we recognize objects by matching the visual information with internally stored viewpoint-specific exemplars, or *prototypes*; the brain stores a number of key views of each object (Edelman & Buelthoff, 1992; Edelman, 1995). This is the image-based object memory theory introduced at the start of this chapter. The views are not simple snapshots; however, they allow recognition despite simple geometric distortions of the image that occur in perspective transformation. This explains why object perception survives the kinds of geometric distortions that occur when a picture is viewed and tilted with respect to the observer.

There are strict limits on the extent to which we can change an image before recognition problems occur. Palmer et al. (1981) had observers rate how well pictures taken from different perspectives resembled the object depicted. The results showed strongly that certain views were judged more typical than others (see Figure 8.17). Moreover, this had a large effect on the amount of time it took subjects to name the object shown. Other studies have revealed that objects are named faster when they are upright (Jolicoer, 1985), but changing the size of the represented object has a relatively small effect. Also, numerous studies show impaired face recognition if the faces are shown upside down (Rhodes, 1995).

> **[G8.16]** To make a visual image that represents a class of things, use a canonical example in its normal orientation displayed from a typical viewpoint, but only if a suitable exemplar exists.

There are many cases where simple images cannot be used to represent categories of objects. One reason is that most things belong to many overlapping sets of categories, and many categories do not have canonical object representations. Consider the category of pet. A pet can be a goldfish, an insect, or a snake, as well as the more typical dogs and cats. No simple sketch can represent all of these, as they do not share a canonical set of visual features. Some abstract categories are even more difficult. The philosopher Wittgenstein (1953) used the example of games to argue that categories should be thought of as loosely associated bundles of properties, rather than concepts that can be defined by a few formal rules. Board games, sports such as soccer, and games such as charades all belong to the game category. Such categories are very difficult to formally pin down, and, like pets, have no canonical representation.

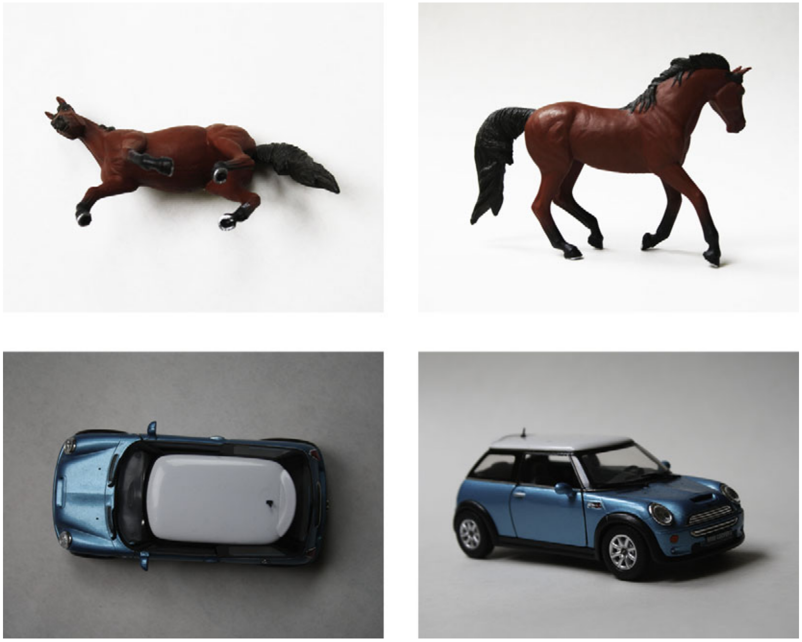


Figure 8.17 Noncanonical and canonical views of a horse and a car.

What does this have to do with visualization? In many diagrams and charts it is common to use pictorial symbols to represent various kinds of categorical information. This is especially true of so-called infographics. Stacks of little house-shaped symbols and stacks of little car-shaped symbols may be used to represent the rates of home and car ownership in different countries. A hamburger is sometimes used to represent junk food in a chart. Broccoli has achieved similar status as a symbol for healthy food. Figure 8.21 shows an example of these symbols used in an information graphic. In this case, the effectiveness of hamburgers and broccoli does not have to do with their having a canonical *visual* form in the Roschean sense. Rather, if they are effective it is because of their culturally determined status as symbols for these categories.

Concept Mapping

Researchers in the field of information visualization have put considerable effort into creating visual representations of ideas and abstract concepts. These can be considered as potential visual thinking tools.

Concept Maps and Mind Maps

A technique that is promoted as a learning aid for students is called *mind mapping* (Jonassen et al., 1993). It consists of sketching out links between concepts, as illustrated

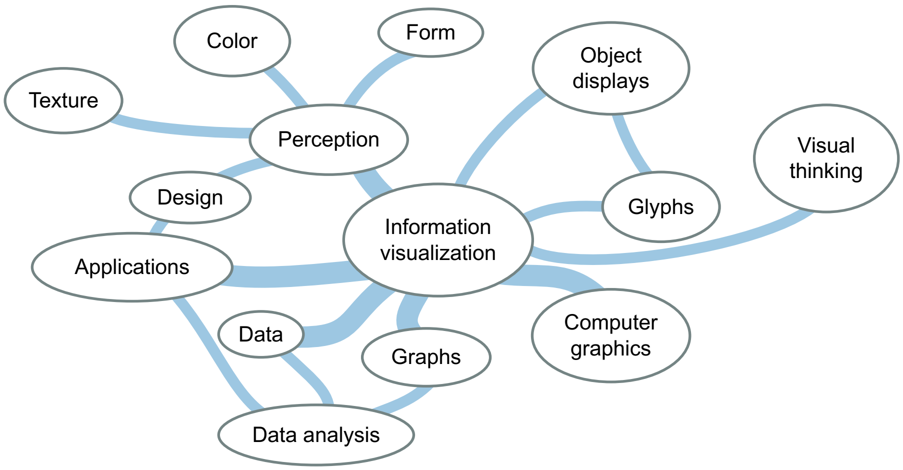


Figure 8.18 A concept map surrounding the concept "information visualization."

in Figure 8.18. Usually, such maps are constructed informally by sketching them on paper, but computer-based tools also exist. Essentially, a concept map is a type of node–link diagram in which the nodes represent concepts and the links represent relationships between concepts. An individual can use a concept map as a tool for organizing his or her own personal concept structure, and it may reveal patterns of relationships between ideas that had not been evident when the concepts were stored internally. A concept map can also be constructed as a group exercise, in which case it becomes a tool for building a common understanding.

Most educational theory suggests that in order to learn concepts it is important that students actively work to integrate new ideas into the framework provided by their existing knowledge (Willis, 1995). This is the central theme of constructivist education theory that has its roots in the work of the Russian psychologist Lev Vygotsky (1978). Constructivism also emphasizes the social roots of knowledge and that much of our concept formation is shaped by social pressures (Karagiorgi & Symeou, 2005).

Superficially, concept maps would seem to fit well with constructivist theory. To construct such a map, students must actively draw out links between various concepts as they understand them. The problem is that the cognitive engagement tends to be somewhat superficial, since it does not require that students think about the *nature of the links*. For example, simply knowing that there is a link between disease and urban living is of marginal value, but if we know something about how diseases are propagated then we can design better sanitation systems. A more elaborate concept might be used to trace out propagation mechanisms, but written notes may be more effective for the reasons outlined in Chapter 9.

The best note-taking techniques appear to be hybrids combining concept organization techniques (using connecting lines and boxes) with more detailed textual information

(Novak, 1981). Other structured note-taking methods can be effective, such as arranging ideas in a matrix (Kiewra, 1999).

There are other reasons for mapping concepts into a visual space. Recently, sophisticated computer algorithms have been developed to parse large text databases in order to understand how ideas, as expressed in society at large, are related to one another and how they develop over time. For example, the SPIRE system creates a classification of documents with respect to a keyword query and can be applied to databases consisting of hundreds of thousands of documents (Wise et al., 1995). The result of the SPIRE algorithm is a set of vectors in an n-dimensional space. To help people understand the resulting clusters of documents, Wise et al. created a visualization called a *ThemeScape*, which shows the two most important dimensions as a kind of data landscape. This is illustrated in Figure 8.19. Flags on top of hills label and identify the largest clusters of documents in this space. Essentially, a ThemeScape uses the two most significant dimensions of the abstract data space to create a smoothed 2D histogram. Spatial proximity and salience show the major concentrations of information and, to some extent, their relationships. This kind of display will be useful when two dimensions really do capture most of the variability in the data.

Other visualizations have been designed to map out the temporal evolution of larger themes in text databases. ThemeRiver is an application developed by Havre et al. (2000) designed to show how ideas become more prevalent over time, and then fade away. It has been used to show the temporal trajectory of major news stories.

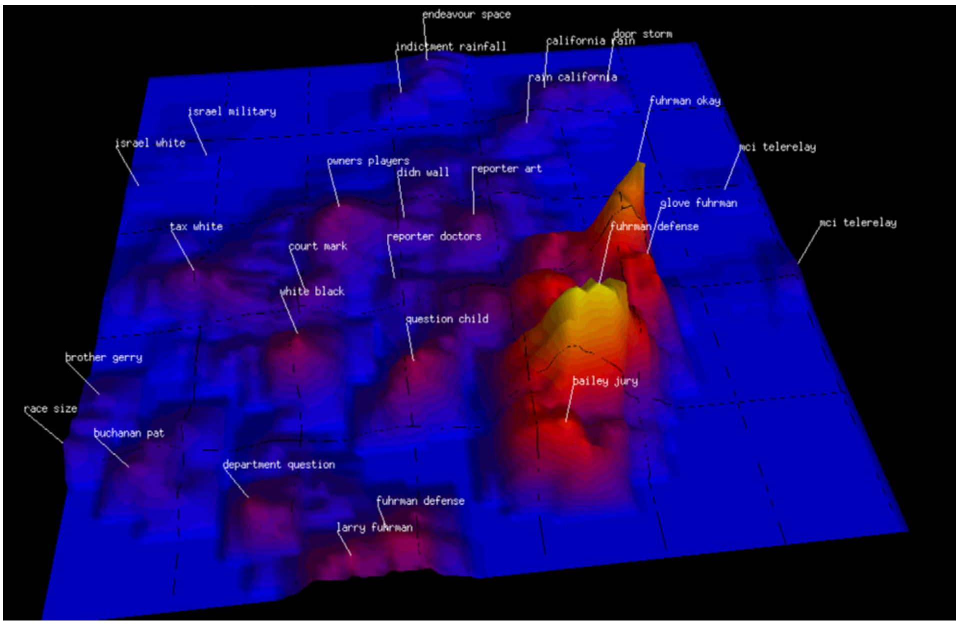


Figure 8.19 An entire week of CNN news stories is summarized in a ThemeScape. (*From Wise et al. (1995). Reproduced with permission.*)

Visualizations such as ThemeScape and ThemeRiver can perhaps be used to understand the *zeitgeist* of the time. Politicians want to know which issues are receiving the most press attention and these displays may help. But, like concept maps, both displays provide only the most superficial information about the relationships of ideas. In addition, because very high-dimensional data has been mapped into a low-dimensional space, proximities between concepts are only sometimes meaningful.

Other systems have been developed to map human knowledge into a node–link diagram. Bollen et al. (2009) used a very large university database derived from Internet searches carried out by university students and faculty. Their goal was to understand which areas of scholarly endeavor are most closely related. Their algorithm judged there to be a connection between disciplines when there were information selections (via mouse clicks) in different disciplines by the same person, close together in time. This is called *clickstream* data. The resulting map of knowledge is shown in Figure 8.20. It shows the physical sciences to the right and social sciences

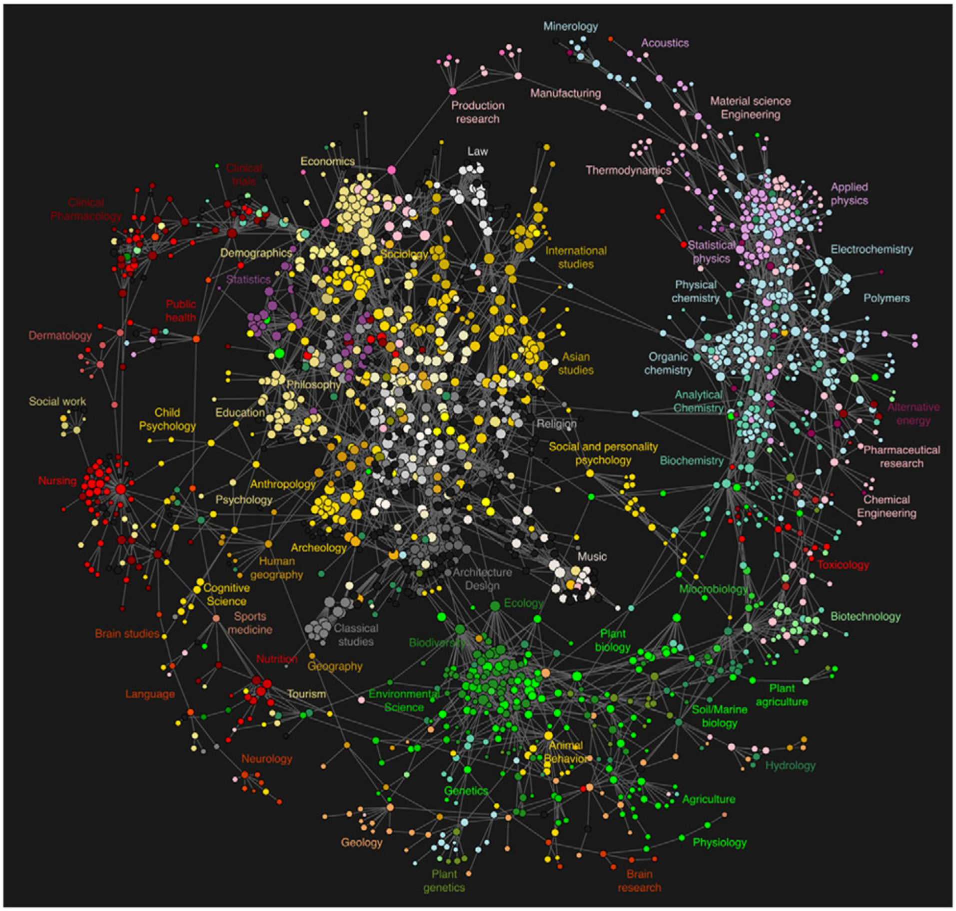


Figure 8.20 A diagram showing the links between academic disciplines using clickstream data. (*From Bollen et al. (2009). Reproduced with permission.*)

and clinical areas to the left, with the arts in the center. This particular layout is arbitrary, an artifact of the algorithm, but the connections between areas is meaningful. Highly interconnected areas mean that scholars were researching in both disciplines. Such a map might be used by university administrators thinking about the logical structure of faculties, or it might be used to organize government funding agencies according to the most closely linked scholarly areas.

Iconic Images versus Words versus Abstract Symbols

We have choices when creating a visualization that requires symbols. We can use abstract visual symbols such as triangles, squares, or circles; we can use pictorial icons, such as an image of broccoli to represent "vegetables"; or we can use words or phrases. The best solution depends on a number of factors—the purpose of the visualization, the number of data points and how dense they are, and the availability of canonical images. For example, if the quantity represented is something like the price/earnings ratio of a stock, then pictorial icons are not available.

In general, pictorial icons are best used when the purpose of a visualization is pedagogical, and they are not intended for the data analyst who usually insists on far more detailed information. The reason for using the pictorial icon in an infographic is cognitive efficiency, especially for the occasional user. Using an image to represent a data object means that it is not necessary to consult a key to get its category, ensuring one less step in the process of understanding. Infographics are often designed for rapid understanding by people who may have only a marginal interest in the content—for example, the readers of magazine or newspaper articles. A general audience may lack familiarity with more specialized (and abstract) charting conventions, so reducing a step can easily make the difference between something that is ignored and something that provides information. Also, in infographics the information content is usually quite low, so there is more space available for images.

[G8.17] Consider using pictorial icons for pedagogical purposes in infographics. Use them only where a canonical or culturally defined image is available.

When using visual symbols as glyphs to display quantity we must beware of the potential distortion inherent in varying size to display relative quantity; linear coding using multiples is generally preferable. Using the stacked hamburgers, as shown in Figure 8.21, is likely better than using a single big hamburger and a single big broccoli, each sized to represent some quantity. As discussed in Chapter 5 (guideline G5.17), it is particularly disastrous to use the volume of an object to represent a numerical quantity.

The choice of abstract symbols versus labeled points and regions should also be made on the basis of cognitive efficiency. Abstract symbols are effective when there are many data points belonging to a few different categories. Abstract symbols can be

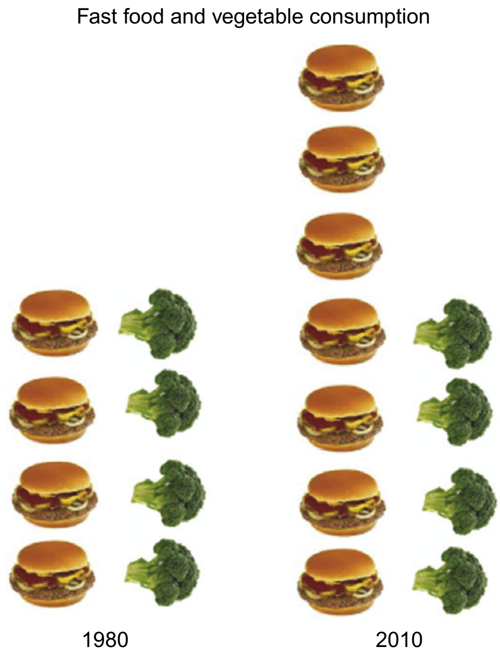


Figure 8.21 In infographics, repeated pictorial icons are often used to represent quantity.

more compact than pictorial icons. Also, if visual clustering is important, the effective use of low-level visual features discussed in Chapters 5 and 6 becomes critical.

> **[G8.18]** When a large number of data points must be represented in a visualization, use symbols instead of words or pictorial icons.

Written and spoken language has orders of magnitude more category labels than there are standardized pictorial icons. This means that words must be chosen over pictorial icons in most cases, but diagrams densely populated with printed words can become unintelligible. Directly labeling objects in visualizations using words is most suitable when there is a single member for each category, or only a few, and where the category density is low.

> **[G8.19]** Use words directly on the chart where the number of symbolic objects in each category is relatively few and where space is available.

Static Links

When text is integrated into a static diagram, the Gestalt principles discussed in Chapter 6 apply, as Figure 8.22 shows. Simple proximity is commonly used in labeling maps. A line drawn around the object and text creates a common region. A line or common region can

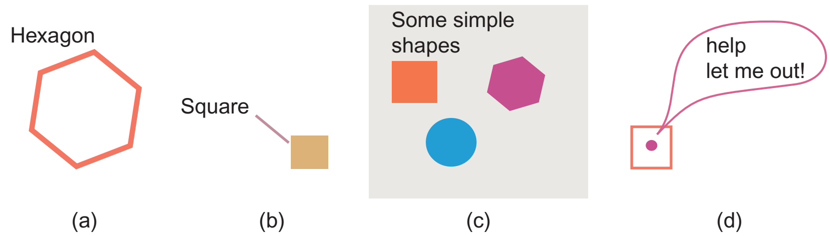


Figure 8.22 Gestalt principles used to guide the linking of text and graphics: (a) Proximity. (b) Continuity/connectedness. (c) Common region. (d) Common region combined with connectedness.

also be used to associate groups of objects with a particular label. Arrows and speech balloons linking text and graphics also apply the principle of connectedness.

> **[G8.20]** Use Gestalt principles of proximity, connectedness, and common region to associate written labels with graphical elements.

Scenes and Scene Gist

Rapid categorization occurs with scenes as well as visual objects. If you flip channels on a TV, within 100 ms of the new image appearing your brain will have classified it as being a beach scene, a street scene, an interior, a store, a bar, an office, or any one of many different types of scenes. Moreover, your brain will be primed for activities within that particular scene; in particular, the sequences of eye movements needed to find a certain detail in a specific scene will be facilitated (Oliva et al., 2003; Oliva, 2005).

In the perception of gist, the broad spatial layout of a scene is identified in addition to the identification of its basic-level category (Potter, 1976). Also, a cognitive framework may be activated that includes priming the actions that may be useful for dealing with the new information.

Scene gist is important in data visualization because what we see depends enormously on the context. The gist of familiar visual displays will be processed just as fast as the gist of natural scenes, and it will have a similar effect on our response biases. The expectations and priming of the brain will have a huge effect, especially in cases where a rapid response is required. This provides another argument for consistency of representation for common types of visualization.

Priming, Categorization, and Trace Theory

We now return to the topic of priming and discuss how it affects categorization. Priming can have both positive and negative consequences with regard to categorization.

Figure 8.23 Pairs of sketches developed by Ratcliff and McKoon (1996). Each pair has visual similarity, but the objects represented have very different uses.

In some ways, priming can be regarded as a biasing of perception. Ratcliff and McKoon (1996) made sketches of pairs of objects that were visually very similar but belonged to very different categories (Figure 8.23). They found normal priming when an image was shown for a second time, a week later, in a rapid naming task; however, when the similar image (within a different category) was shown a week later, naming was actually slowed.

They argued that the result adds support to a trace theory of cognitive skill learning. According to this theory, whenever we successfully complete a cognitive activity, such as identifying an object, all the various neural pathways that were activated at the time become strengthened, so that the next time the same object is presented, processing is facilitated. But, strengthening a set of pathways inevitably means that alternative pathways are less likely to be activated in similar circumstances, introducing a form of bias. One of the implications is that priming, and indeed all categorization, is a two-edged sword. Priming and categorization can lead to errors. Once we learn a particular interpretation of a pattern, we get faster at classifying it in a certain way, automatically classifying it at a glance, but this means that we are less likely to come up with alternative interpretations.

We shall return to the issue of priming, and sensory learning in general, in the following chapters as we begin to consider the process of visual thinking.

Conclusion

In this chapter, we have moved well beyond thinking of perception only as the extraction of information from what is imaged on the retina. Once an object is identified as *something*, as opposed to an abstract collection of features and colors, a range of associations is automatically activated in the brain, and these associations are what make up most of what we subjectively perceive. Some of these cognitive responses are in the visual system; others are in the language centers and in the regions that control actions. To illustrate this point, Figure 8.24 shows the range of cognitive activities that might occur when someone looks at a diagram of the human blood circulation system. They are fixating on, and trying to understand, a part of the diagram that schematically depicts the heart. A small amount of information is held in visual working memory, consisting of visual patterns relating to the left and right chambers of the heart. The overall topology (chambers are part of heart) and shape have also been processed and held in working memory. As part of the mental act of identification, the verbal

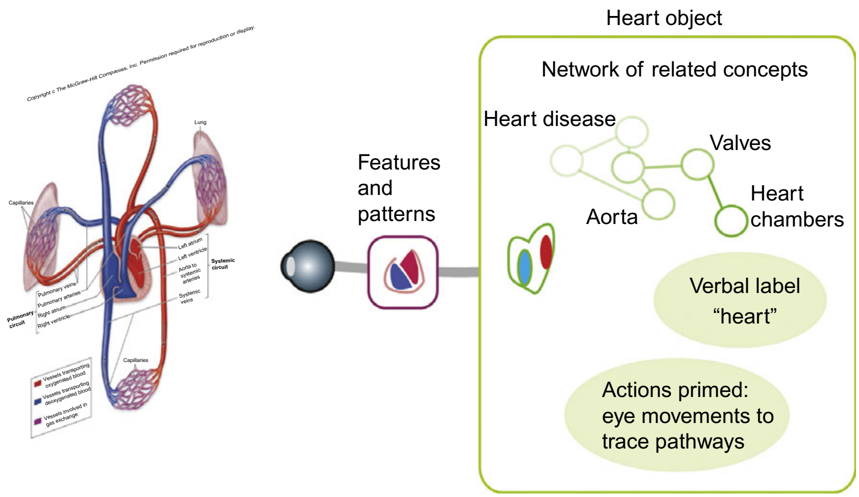


Figure 8.24 The percept of an object consists mostly of information stored in memory that has been activated by the visual information; this remains linked to a relatively small amount of information coming from the external world.

label "heart" becomes activated, as well as a network of related concepts. Concepts further from the current focus of cognitive attention are brought to a state of readiness. Simultaneously, eye-movement programming systems are brought to a state of readiness to do such things as trace the pathways, as represented in the diagram. All of this visual and nonvisual activity is exquisitely focused on the cognitive task of the moment. Little or no irrelevant information is processed. It is this ability to flexibly combine diverse types of information that makes human visual thinking so powerful.

CHAPTER NINE

Images, Narrative, and Gestures for Explanation

Most of this book up to this point has been about how to display data for the data analyst. It has been about data *exploration* and how to present data so that new things can be discovered. But there is another major use of visualization, and that is the *explanation* of patterns in data. Once something has been understood by someone, that person must usually present those results to other people, with the goal of convincing them that one interpretation or another is correct. The cognitive processes involved (i.e., interpreting data and explaining data) are very different.

One way of elucidating this difference is to think about who or what is in control of the cognitive sequence. The process of visual thinking can be thought of as a kind of collaborative dialogue between a person and a visual representation, especially if the visualization is computer based and interactive. In the case of data exploration, the cognitive processes of the data analyst are in control. Conversely, in the case of the presentation of results, it is the presenter, the author of an article, or the designer of a poster who is, or should be, in control of the cognitive thread (Ware, 2009). The audience takes in a series of visual patterns and words in a sequence that is controlled by the presenter. This material will occupy most of the capacity of both visual and verbal working memories, and any attention controlling sequence of information is a form of *narrative*. In this chapter, we will explore the different ways that images and words can be used to create narrative structure.

We will address the problem of integrating visual and verbal materials in multimedia presentations. We will also address the particularly thorny but interesting problem of whether or not we should be using visual languages to program computers. Although

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computers are rapidly becoming common in every household, very few people are programmers, and it has been suggested that visual programming languages may make it easier for "nonprogrammers" to program computers.

The Nature of Language

Before going on to consider whether or not we can or should have such a thing as a visual language, we need to think about the nature of language. Noam Chomsky revolutionized the study of natural language because he showed that there are aspects of the syntactic structure of language that generalize across cultures (Chomsky, 1965). A central theme of his work is the concept that there are "deep structures" of language, representing innate cognitive abilities based on inherited neural structures. In many ways, this work forms the basis of modern linguistics. The fact that Chomsky's analysis of language is also a cornerstone of the theory of computer languages lends support to the idea that natural languages and computer languages have the same cognitive basis.

Other evidence supports the innateness theory. There is a critical period for normal language development that extends to about age 10; however, language is most easily acquired in the interval from birth to age 3 or 4. If we do not obtain fluency in some language in our early years, we will never become fluent in any language. Also, there are areas in the brain specialized for spoken language production (Broca's area) and language comprehension (Wernicke's area). These are distinct from the areas associated with visual processing, suggesting that language processing, whatever it is, is distinct from visual processing.

Sign Language

Despite the evidence for special brain areas, being verbal is not a defining characteristic of natural language capacity. Sign languages are interesting because they are examples of true visual languages. If we do not acquire sign languages early in life, we will never become very adept at using them. Sign languages are not translations of spoken languages, but are independent, having their own grammars. Groups of deaf children spontaneously develop rich sign languages that have the same deep structures and grammatical patterns as spoken language. These languages are as syntactically rich and expressive as spoken language (Goldin-Meadow & Mylander, 1998).

Sign languages grew out of the communities of deaf children and adults that were established in the 19th century, arising spontaneously from the interactions of deaf children with one another. Sign languages are so robust that they thrived despite efforts of well-meaning teachers to suppress them in favor of lip reading—a far more limiting channel of communication. There are many sign languages; British sign language is a radically different language from American sign language, and the sign language of France is similarly different from the sign language of francophone Quebec (Armstrong et al., 1994).

Although in spoken languages words do not resemble the things they reference (with a few rare exceptions), signs are partially based on similarity; for example, see the signs for a tree illustrated in Figure 9.1. Sign languages have evolved rapidly. The pattern appears to be that a sign is originally created on the basis of a form of similarity in the shape and motion of the gesture, but over time the sign becomes more abstract and similarity becomes less and less important (Deuchar, 1990). It is also the case that even

Figure 9.1 Three different sign language representations of a tree. Note that they are all very different and all incorporate motion. (*From* Bellugi & Klima (1976)*. Reproduced with permission.*)

signs apparently based on similarity are only recognized correctly about 10% of the time without instruction, and many signs are fully abstract.

Even though sign language is understood visually and produced through hand gestures, the same brain areas are involved in comprehension and production as are involved in speech comprehensions and production (Emmorey & McCullough, 2009). This tells us that language has distinct brain subsystems that function in the same roles, no matter what the sensory input or means of production.

Language Is Dynamic and Distributed over Time

We take in spoken, written, and sign language *serially*; it can take a few seconds to hear or read a short sentence. Armstrong et al. (1994) argued that, in important ways, spoken language is essentially dynamic. Verbal expression does not consist of a set of fixed, discrete sounds; it is more accurately described as a set of vocal gestures producing dynamically changing sound patterns. The hand gestures of sign language are also dynamic, even when denoting static objects, as Figure 9.1 illustrates. There is a dynamic and inherently temporal phrasing at the syntactic level in the sequential structure of nouns and verbs. Also, written language, although it comes in initially through the visual channel, is transformed into a sequence of mentally recreated dynamic utterances when it is read. In contrast with the dynamic, temporally ordered nature of language, relatively large sections of static pictures and diagrams can be understood *in parallel*. We can comprehend the gist of a complex visual structure in a fraction of a second, based on a single glance.

Is Visual Programming a Good Idea?

The difficulty of writing and understanding computer programs has led to the development of a number of so-called visual languages in the hope that these can make the task easier; however, we must be very careful in discussing these as languages. Visual programming languages are mostly static diagramming systems, so different from spoken languages that using the term *language* for both can be more misleading than helpful. There is a case to be made that computer programming languages have more in common with natural language processing than with visual processing, and that for this reason, programming is better done using methods that relate more closely to natural language.

Consider the following instructions that might be given to a mailroom clerk:

> Take a letter from the top of the In tray.
>
> Put a stamp on it.
>
> Put the letter in the Out tray.
>
> Continue until all the letters have stamps on them.

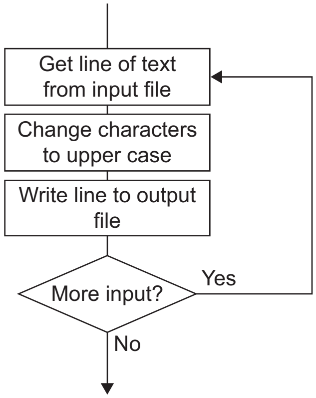

Figure 9.2 A flowchart is often a poor way to represent information that can be readily expressed in natural language-like pseudocode.

This is very like the following short program, which beginning programmers are often asked to write:

```
Repeat
    get a line of text from the input file
    change all the lowercase letters to uppercase
    write the line to the output file
Until (there is no more input)
```

This example program can also be expressed in the form of a diagram called a flowchart (see Figure 9.2).

Flowcharts provide a salutary lesson to those who design visual programming languages. Flowcharts were once part of every introductory programming text, and it was often a contractual requirement that large bodies of software be documented with flowcharts describing the code structure. Once almost universally applied, flowcharts are now almost defunct. Why did flowcharts fail? It seems reasonable to attribute this to a lack of commonality with natural language.

Written and spoken languages, as well as sign languages, are packed with words such as *if*, *else*, *not*, *while*, *but*, *maybe*, *perhaps*, *probably*, and *unlikely*. These provide external manifestations of the logical structure of human thought (Pinker, 2007). We learn the skills of communication and refine our thinking skills early in life when we learn to talk. Using natural language-like pseudocode transfers these skills we already have gained in expressing logic through natural language.

A graphical flowchart representing the same program must be *translated* before it can be interpreted in the natural language processing centers. If, as infants, we learned to communicate by drawing diagrams on paper and if society had developed a structured language for this purpose, then visual programming would make sense, but this is not the case.

Nevertheless, some types of information are much better described in the form of diagrams. A second example illustrates this. Suppose that we wish to express a set of propositions about the management hierarchy of a small company.

Jane is Jim's boss.

Jim is Joe's boss.

Anne works for Jane.

Mark works for Jim.

Anne is Mary's boss.

Anne is Mike's boss.

This pattern of relationships is far more clearly expressed in a diagram, as shown in Figure 9.3. These two examples suggest that visual language, in the form of static diagrams, has certain expressive capabilities that are very different from, and perhaps complementary to, natural language. Diagrams should be used to express structural relationships among program elements, whereas words should be used to express detailed procedural logic.

Throughout this book it has been argued that the strength of visualization is that the perceptual representation of certain types of information can be easily understood. Logical constructs do not appear to constitute one of the types of information for which a natural visual representation exists. Also, although the existence of sign languages suggests that there *can* be visual analogs to natural language, the principle of arbitrariness still applies, so there is no advantage to this form or representation. On balance, the evidence suggests that the detailed logic of programming is best done using methods that rely on words more than graphical codes. Accordingly, we propose the following two broad principles:

[G9.1] Use methods based on natural language (as opposed to visual pattern perception) to express detailed program logic.

[G9.2] Graphical elements, rather than words, should be used to show structural relationships, such as links between entities and groups of entities.

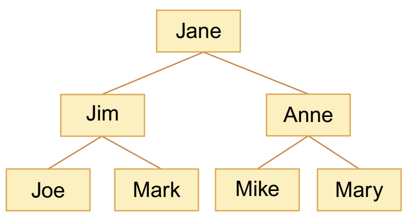

Figure 9.3 A simple organization chart showing the management structure.

None of the above should be taken as an attack on visual programming environments, such as Microsoft® Visual Basic® or Borland's Delphi, but it is worth noting that these are hybrids, as they are far from purely visual. They have many words in their user interfaces, and the way in which programming is done is mixed; some operations are done by connecting boxes, but others require text entry.

Images versus Sentences and Paragraphs

The greatest advantage of words over images and diagrams, either static or dynamic, is that spoken and written natural language is ubiquitous. It is by far the most elaborate, complete, and widely shared system of symbols that we have available. For this reason alone, it is only when there is a clear advantage that visual techniques are preferred. That said, images have clear advantages for certain kinds of information, and a combination of images and words will often be best. A visualization designer has the task of deciding whether to represent information visually, using words, or both. Other, related choices involve the selection of static or moving images and spoken or written text. If both words and images are used, methods for linking them must be selected. Useful reviews of cognitive studies that bear on these issues have been summarized and applied to multimedia design by a number of authors, including Strothotte and Strothotte (1997), Najjar (1998), and Faraday (1998). What follows is a summary of some of the key findings, beginning with the issue of when to use images vs. words separately and in combination.

We have been discussing the special case of programming languages, but the same principles apply in general to the question of whether to display information graphically or with text. Text is better than graphics for conveying abstract concepts (Najjar, 1998), and procedural information is best provided using text or spoken language, or sometimes text integrated with images (Chandler & Sweller, 1991).

We can begin by proposing a more general version of guideline G9.1.

> **[G9.3]** Use methods based on natural language (as opposed to visual pattern perception) to represent abstract concepts.

Of course, it is important that the information be *well* presented, no matter what the medium. Visual information must be meaningful and capable of incorporation into a cognitive framework for a visual advantage to be realized (Bower et al., 1975).

There are also design considerations relating to the viewing time for images. It takes time to scan a complex diagram for its details. Only a little information is extracted in the first glance. A number of studies support the idea that we first comprehend the shape and overall structure of an object, and then we comprehend the details (Price & Humphreys, 1989; Venturino & Gagnon, 1992). Because of this, simple line drawings may be most effective for quick exposures.

Links between Images and Words

The central claim of multimedia theory is that providing information in more than one medium of communication will lead to better understanding (Mousavi et al., 1995). Mayer et al. (1999) and others have translated this into a theory based on dual coding. They suggest that if active processing of related material takes place in both visual and verbal cognitive subsystems, learning will be better. It is claimed that duplicate coding of information in more than one modality will be more effective than single-modality coding. The theory also holds that it is not sufficient for material to be simply presented and passively absorbed; it is critical that both visual and verbal representation be actively constructed, together with the connections between them.

Supporting multimedia theory, studies have shown that images and words in combination are often more effective than either in isolation (Wadill & McDaniel, 1992; Faraday & Sutcliffe, 1997). Faraday and Sutcliffe (1997) found that propositions given with a combination of imagery and speech were recalled better than propositions given only through images. Faraday and Sutcliffe (1999) showed that multimedia documents with frequent and explicit links between text and images can lead to better comprehension. Fach and Strothotte (1994) theorized that using graphical connecting devices between text and imagery can explicitly form cross-links between visual and verbal associative memory structures. Care should be taken in linking words and images. For obvious reasons, it is important that words be associated with the appropriate images. These links between the two kinds of information can be static, as in the case of text and diagrams, or dynamic, as in the case of animations and spoken words. There can be a two-way synergy between text and images.

Despite these studies, there is little or no support for the claim that providing information in both images and words is better than providing information in either medium. None of the early studies actually presented the *same* information in both media (Mayer et al., 2005). Showing a picture of a pile containing apples, oranges, and bananas is not the same as showing the word *fruit*. But, there is a considerable advantage in choosing the most appropriate kind of representation for elements of a data set, and often this will involve a mixed-media representation; some information is best represented using words, whereas other information is best represented using lines, textures, and colored regions. Of course, it is essential that different types of representation be clearly and effectively linked. A much better multimedia principle is the following:

> **[G9.4]** To represent complex information, separate out components according to which medium is most efficient for each display—that is, *images*, moving or static, or *words*, written or spoken. Present each kind of information accordingly. Use the most cognitively efficient linking techniques to integrate the different kinds of information.

We now turn our attention to efficient linking methods.

Integrating Visual and Verbal and the Narrative Thread

In a textbook, written words must be linked with static diagrams, whereas in a lecture written words, spoken words, static images, and moving images are all choices.

Linking Text with Graphical Elements of Diagrams

Beyond merely attaching text labels to parts of diagrams, there is the possibility of integrating more complex procedural information. Chandler and Sweller (1991) showed that instructional procedures for testing an electrical system were understood better if blocks of text were integrated with the diagram, as shown in Figure 9.4. In this way, process steps could be read immediately adjacent to the relevant visual information. Sweller et al. (1990) used the concept of limited-capacity working memory to explain these and similar results. They argued that when the information is integrated there is a reduced need to store information temporarily while switching back and forth between locations.

> **[G9.5]** Place explanatory text as close as possible to the related parts of a diagram, and use a graphical linking method.

At this point, it is worth commenting that the above guideline is not followed in most textbooks, and the one you are reading is no exception. This is because of the constraints of the publishing industry. Textbook layout is completely out of the hands of the author, making it extremely difficult to carefully integrate the words and graphics (Ware, 2008). As a result, text and figures are frequently separated by a few pages, leading to inevitable decline in cognitive efficiency.

Gestures as Linking Devices in Verbal Presentations

Someone giving a talk has the choice of putting the words on the screen or speaking them. If words are on the screen, however, the presenter loses control of the cognitive thread. Audience members will inevitably read ahead, and usually what they are thinking about will not correspond well to what the speaker is saying or to the parts of the images the speaker is pointing at. In addition, there is a clear cognitive efficiency to verbal presentation (as opposed to text) combined with images. Someone cannot read and look at part of a diagram at the same time, but they can listen to verbal information and look at part of a diagram simultaneously (Mousavi et al., 1995).

> **[G9.6]** When making presentations, spoken information, rather than text information, should accompany images.

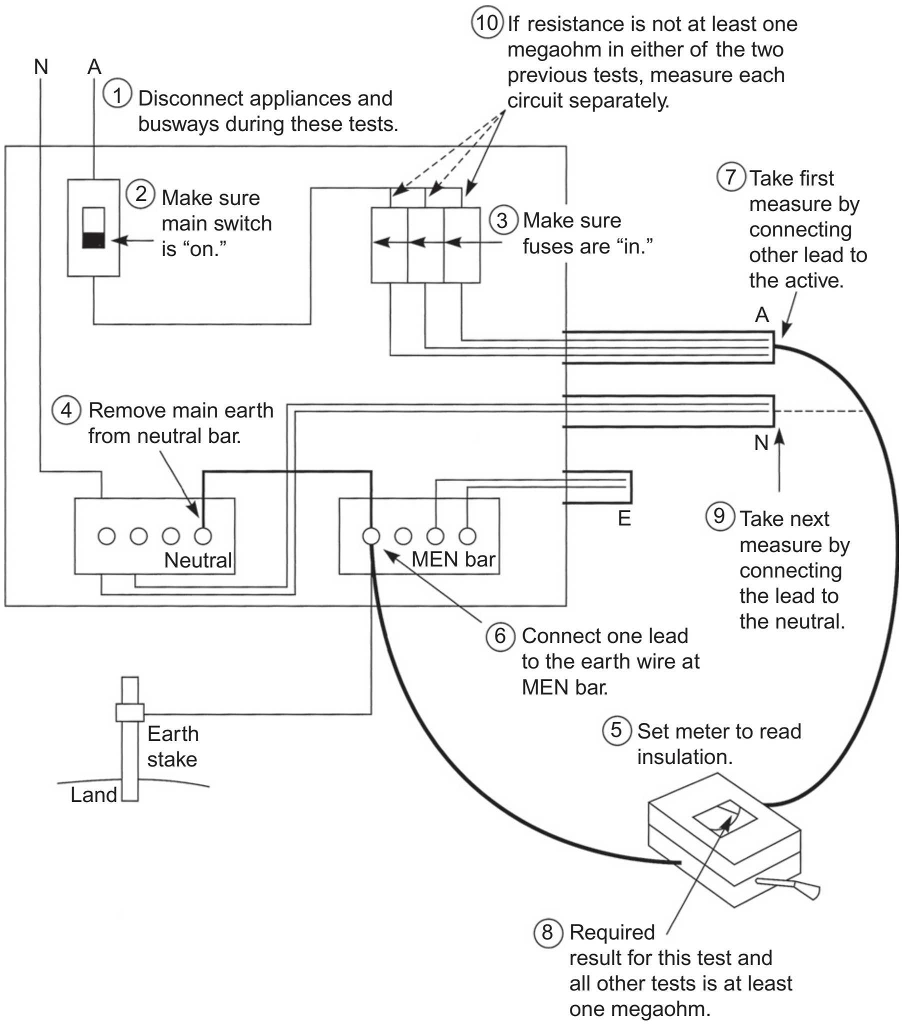

Figure 9.4 An illustration used in a study by Chandler and Sweller (1991). A sequence of short paragraphs is integrated with the diagram to show how to conduct an electrical testing procedure. (*Reprinted with permission*.)

Deixis

The act of indicating something by pointing is called a *deictic gesture* in human communication theory. Often such a gesture is combined with speech so that it links the subject of a spoken sentence with a visual reference. When people engage in conversation, they sometimes indicate the subject or object in a sentence by pointing with a finger, glancing, or nodding in a particular direction. For example, a shopper might say, "Give me that one," while pointing at a particular wedge of cheese at a delicatessen counter.

The deictic gesture is considered to be the most elementary of linguistic acts. A child can point to something desirable, usually long before she can ask for it verbally, and even adults frequently point to things they wish to be given without uttering a word. Deixis can be accomplished with a glance, a nod of the head, or a change in body orientation. It can be enhanced by using a tool, such as a straight rod. Deixis has its own rich vocabulary; for example, an encircling gesture can indicate an entire group of objects or a region of space (Levelt et al., 1985; Oviatt et al., 1997), and a flutter of the hand may add uncertainty to the bounded region.

To give a name to a visual object, we often point and speak its name. Teachers will talk through a diagram, making a series of linking deictic gestures. To explain a diagram of the respiratory system, a teacher might say, "This tube connecting the larynx to the bronchial pathways in the lungs is called the trachea," with a gesture toward each of the important parts.

Deictic techniques can be used to bridge the gap between visual imagery and spoken language. Some shared computer environments are designed to allow people at remote locations to work together while developing documents and drawings. Gutwin et al. (1996) observed that, in these systems, voice communication and shared cursors are the critical components in maintaining dialogue. Transmitting an image of the person speaking is usually much less valuable. Another major advantage of combining gestures with visual media is that this multimodal communication results in fewer misunderstandings (Oviatt et al., 1997; Oviatt, 1999), especially when English is not the speaker's native language.

> **[G9.7]** Use some form of deixis, such as pointing with a hand or an arrow, or timely highlighting to link spoken words and images.

Oviatt et al. (1997) showed that, given the opportunity, people like to point and talk at the same time when discussing maps. They studied the ordering of events in a multimodal interface to a mapping system in which a user could both point deictically and speak while instructing another person in a planning task using a shared map. The instructor might say something like "Add a park here" or "Erase this line" while pointing to regions of the map. One of their findings was that pointing generally preceded speech; the instructor would point to something and then talk about it.

> **[G9.8]** If spoken words are to be integrated with visual information, the relevant part of the visualization should be highlighted just before the start of the accompanying speech segment.

Web-based presentation enables a form of deixis with textual material. Links can be made by mouse clicks. In a study of eye movements, Faraday and Sutcliffe (1999) found that people would read a sentence, then look for the reference in an accompanying diagram. Based on this finding, they created a method for making it easy for users to make the appropriate connections. A button at the end of each sentence caused the relevant part of the image to be highlighted or animated in some way, thus enabling readers to switch attention rapidly to the correct part of the diagram. They showed that this did indeed result in greater understanding.

Symbolic Gestures

In everyday life, we use a variety of gestures that have symbolic meaning. A raised hand signals that someone should stop moving or talking. A wave of the hand signals farewell or hello. Some symbolic gestures can be descriptive of actions; for example, we might rotate a hand to communicate to someone that they should turn an object. McNeill (1992) called these gestures *kinetographics*. With input devices, such as the Data-Glove, that capture the shape of a user's hand, it is possible to program a computer to interpret a user's hand gestures. This idea has been incorporated into a number of experimental computer interfaces. In a notable study carried out at MIT, researchers explored the powerful combination of hand gestures and speech commands (Thorisson et al., 1992). A person facing the computer screen first asked the system to

> "Make a table."

This caused a table to appear on the floor in the computer visualization. The next command,

> "On the table, place a vase,"

was combined with a gesture placing the fist of one hand on the palm of the other hand to show the relative location of the vase on the table. This caused a vase to appear on top of the table. Next, the command

> "Rotate it like this"

was combined with a twisting motion of the hand, causing the vase to rotate as described by the hand movement.

Full-body sensing devices, such as the Microsoft® Kinect™, make this approach very affordable. Although the use of such devices outside of the realm of video games is still experimental, combining words with gestures may ultimately result in communication that is more effective and less prone to error (Mayer & Sims, 1994).

Expressive Gestures

Gestures can have an expressive dimension in addition to being deictic. Just as a line can be given a variety of qualities by being made thick, thin, jagged, or smooth, so can a gesture be made expressive (McNeill, 1992; Amaya et al., 1996). A particular kind of hand gesture, called a *beat*, sometimes accompanies speech, emphasizing critical elements in a narrative. Bull (1990) studied the way political orators use gestures to add emphasis.

Vigorous gestures usually occurred at the same time as vocal stress. Also, the presence of both vigorous gestures and vocal stress often resulted in applause from the audience. In the domain of multimedia, animated pointers sometimes accompany spoken narrative, but often quite mechanical movements are used to animate the pointer. Perhaps by making pointers more expressive, critical information can be brought out more effectively.

Animated versus Static Presentations

In the early days of multimedia research, extravagant claims were made for the superiority of animated presentations combined with written or spoke text, compared to static presentation of the information. These claims have not withstood careful analysis. A review of the studies carried out by Tversky et al. (2002) found that the majority failed to show advantages of animated over static presentations. Where they did find a difference, it could be attributed to the lack of equivalence of the information presented dynamically versus statically.

In one of the few studies where care was taken to ensure that the *same* information was available in both animated and static presentations, Mayer et al. (2005) found that the static version resulted in better retention of the information and better ability to generalize from the materials, indicating a deeper understanding. To present the static information, they used cartoon like series of frames, with each frame illustrating a key concept. Figure 9.5 shows one of the examples they used. In this case, the goal was to explain how a toilet flushing mechanism works.

KidSim was a visual programming language based on animated characters (Cypher & Smyth, 1995). Rader et al. (1997) carried out an extensive independent evaluation of KidSim in two classrooms over the course of a year. The system was deliberately introduced without explicit teaching of the underlying programming concepts. They found that children rapidly learned the interactions needed to draw animated pictures but failed to gain a deep understanding of the programs. The children often tried to generalize the behavior they saw in ways that the machine did not understand. Students sometimes found it frustrating when they set up conditions they thought should cause some action, with no results.

A study by Palmiter et al. (1991) provided two kinds of instructions for a procedural task; one was an animated demonstration, and the other was a written text. They found that immediately following instruction, the animated demonstration produced better performance, but a week later the results reversed, as those who received written instructions did better. They explained these results by suggesting that in the short term subjects given animated instructions could simply mimic what they had recently seen. In the longer term, the effort of interpreting the written instructions produced a deeper symbolic coding of the information that was better retained over time.

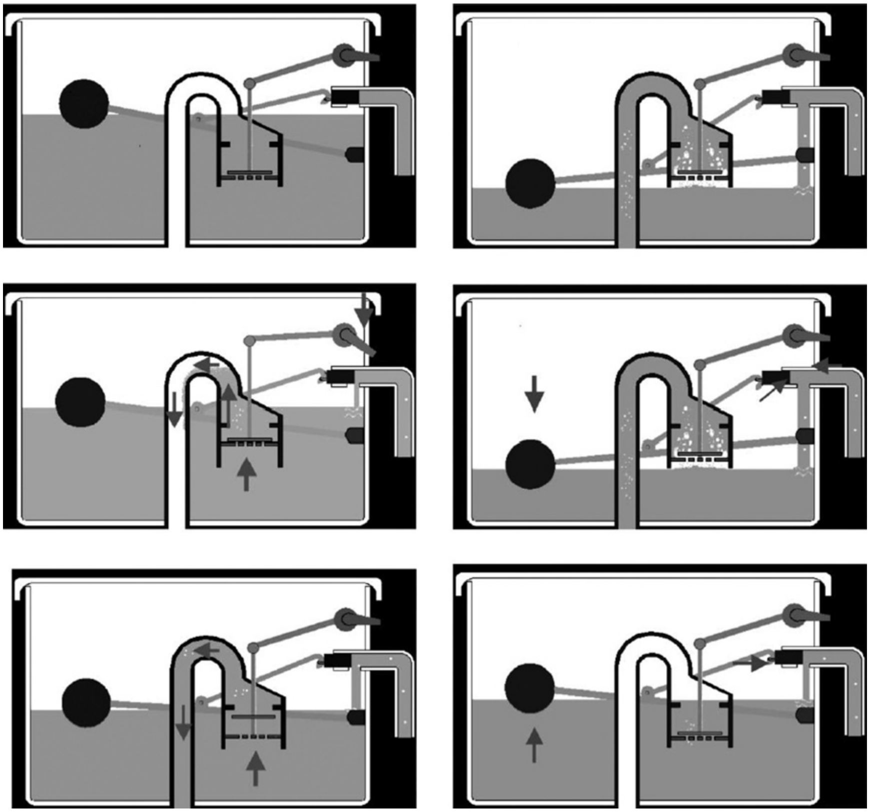

Figure 9.5 One of the explanatory diagrams used in a study by Mayer et al. (2005) to investigate animated versus static diagrams. (*From Mayer et al. (2005). Reproduced with permission.*)

An explanation for the failure to find an advantage for animations can be found in an analysis of the processes involved in constructing meaning. In order to construct a cognitive model explaining a series of events, it is necessary for the learner to construct hypotheses and then test them against the available information. The static diagram may provide better support for this than an animated sequence for a number of reasons. Usually, the key information relating to the hypotheses can be more clearly presented statically, although of course this depends on good design. A static diagram sequence, such as that shown in Figure 9.5, offers access at any time, via eye movements, to the different parts of the explanation, allowing the learner to gain the information at exactly the time it is needed in the process of cognitive model construction (Mayer et al., 2005; Ware, 2009). Also, with static materials, a learner must mentally animate components from one state to the next, and it is precisely this kind of cognitive effort that can promote a deeper understanding (Mayer et al., 2005).

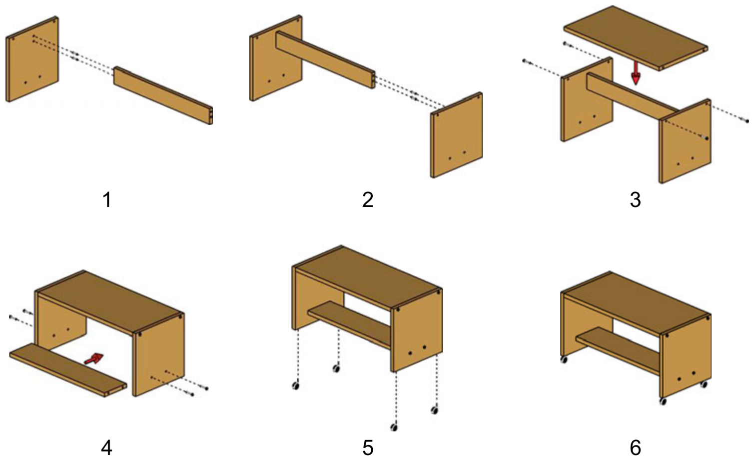

Figure 9.6 An example of an assembly diagram designed according to a set of cognitive best practices developed by Heiser et al. (2004).

Heiser et al. (2004) offer a set of principles for the design of assembly diagrams, derived from an analysis of the task in cognitive terms (see Figure 9.6). Here they are given as guidelines.

> **[G9.9]** Use the following principles when constructing an assembly diagram: (1) A clear sequence of operations should be evident to maintain the narrative sequence. (2) Components should be clearly visible and identifiable. (3) The spatial layout of components should be consistent from one frame to the next. (4) Actions should be illustrated, along with connections between components.

Visual Narrative

Despite the evidence from academic studies, animated visualizations are increasingly developed for television science shows and interactive computer displays. We now turn our attention to how animation may be most effective, while recognizing that research suggests that static representations are likely to be as good as or better than animations.

The silent movies of the 1920s show that narrative can be conveyed visually as well as verbally. This means that the cognitive thread of a viewer can be controlled by getting him to look at particular objects and actions in a particular sequence. When movies are made, it is the job of the director and cinematographer to design sequences of actions and frame camera shots in such a way that viewers are strongly constrained to look at particular objects at particular times, ensuring that their visual working memories will be filled with information in a certain sequence that carries the plot. When the goal is to explain scientific concepts by establishing a sequence of ideas in the minds of an audience, the same techniques may be applied to the visual presentation of information derived from data.

In cinematography, attention is controlled by means of different kinds of camera shots and transitions between them. Establishing shots, zooms, close-ups, and dolly shots, as well as various kinds of transition, are just a few of the commonly applied methods. These are mostly beyond the scope of this book, but only because most of them have not been formally studied by vision scientists; however, anyone wishing to make high-quality science videos would do well to study this craft. Here, we will restrict ourselves to work that has been done by psychologists and researchers working on effective educational visualizations.

Moving the viewpoint in a three-dimensional (3D) visualization can function as a form of narrative control. Obviously, we can only see what is in the camera frame, and large centrally placed objects are more likely to draw attention than peripheral small objects. A virtual camera can be moved from one part of a 3D data space to another, drawing attention to different features. In some complex 3D visualizations, a sequence of shots is spliced together to explain a complex process.

Shot transitions are defined by an instantaneous translation of a camera in space and/or time; the result can be confusion with respect to where and when the viewer feels he is situated. Hochberg and Brooks (1978) developed the concept of *visual momentum* in trying to understand how cinematographers link different camera shots together so the viewer can relate objects seen in one clip with objects seen in the next. As a starting point, they argued that in normal perception people do not take more than a few glances at a simple static scene; following this, the scene "goes dead" visually. In cinematography, the device of the cut enables the director to create a kind of heightened visual awareness, because a new perspective can be provided every second or so. The problem faced by the director is that of maintaining perceptual continuity. If a car travels out of one side of the frame in one scene, it should arrive in the next scene traveling in the same direction; otherwise, the audience may lose track of it and pay attention to something else.

Hochberg (1986) showed that identification of image detail was better when an establishing shot preceded a detail shot than when the reverse ordering was used. This suggests that an overview map should be provided first when an extended spatial environment is being presented. An option that is available in data visualization is to always display a small overview map. The use of an overview map is common in many adventure video games as well as navigation systems used in aircraft or ground vehicles. Such maps are usually small insets that provide a larger spatial context, supplementing the more detailed local map. The same kind of technique can be used with large information spaces. The general problem of providing focus and context is also discussed in Chapter 10.

In the film industry, people are employed to ensure *continuity*; this involves making sure that clothing, makeup, and props are consistent from one cut to another. In visualization, Wickens (1992) proposed the principle of using consistent representations—the same kinds of information should be conveyed with the same colors and symbol shapes.

[G9.10] Use consistent representations from one part of a visualization sequence to the next. The same visual mappings of data must be preserved. This includes presenting similar views of 3D objects.

A second device that can be used to allow viewers to cognitively link one view of a data space to the next is what Wickens (1992) called an *anchor*. Certain visual objects may act as visual reference points, tying one view of a data space to the next. An anchor is a constant, invariant feature of a displayed world. Anchors become reference landmarks in subsequent views. Ideally, when cuts are made from one view to another, several anchors should be visible from the previous frame. One common kind of frame used in visualization are axis marks that show some kind of scale information. A third method for maintaining visual continuity is the idea of an overview map. This is also discussed in the next chapter.

[G9.11] Use graphic devices, such as frames and landmark objects, to help maintain visual continuity from one view of a data space to another.

Animated Images

Despite the evidence that static representations are at least as good as animated representations, researchers have continued to investigate ways that dynamic representations can be made more effective. The problem with animations is that only a short segment is likely to be applicable to a viewer's cognitive modeling processes at any instant. If the sequence is long, much time is wasted replaying it just to get the bit that is currently relevant. One technique designed to help with this is to break explanatory animations into short segments. Each section can be viewed when the user is mentally prepared to engage with that particular aspect of the cognitive task. If it is short, it can easily be replayed multiple times.

In a study of an instructional animation explaining the causes of day and night (based on rotation of the Earth), Hasler et al. (2007) compared three modes of presentation. In the first, the animation was run straight through, although it could be replayed. In the second, stop and start buttons allowed the user to pause and resume play at any time. In the third, the animation was broken into a series of segments, each of which could be independently played. The results showed that both of the interactive modes produced higher test performance with lower cognitive load scores.

> **[G9.12]** Animated instructions should be broken into short meaningful segments. Users should be given a method for playing each segment independently.

It also seems plausible that animation can represent basic concepts in a way that is not possible in static diagrams. The work of researchers such as Michotte (1963), Heider and Simmel (1944), and Rimé et al. (1985), discussed in Chapter 6, shows that people can perceive events such as hitting, pushing, and aggression when geometric shapes are moved in simple ways. None of these things can be expressed with any directness using a static representation, although many of them can be expressed well using words. Animation brings graphics closer to words in expressive capacity.

Possibly the single greatest enhancement of a diagram that can be provided by animation is the ability to express causality (Michotte, 1963). With a static diagram, it is possible to use some device, such as an arrow, to denote a causal relationship between two entities, but the arrowhead is a conventional device that perceptually shows that there is *some* relationship, necessarily causality. The work of Michotte shows that with appropriate animation and timing of events, a causal relationship will be directly and unequivocally perceived.

A final point about animation is that certain visualizations are intended to teach people to perform physical movements—for example, teaching someone a tennis stroke. There is increasing evidence that the brain contains *mirror neurons*. These are cells that respond directly to the actions of others, and they facilitate the perceiver performing those exact same motions (Rizzolatti & Sinigaglia, 2008). This suggests that a clear advantage should be obtained in teaching movements using animation, as opposed to a series of static stills. Based on a study of mechanical troubleshooting, Booher (1975) concluded that an animated description is the best way to convey perceptual motor tasks, but verbal instruction is useful to qualify the information.

> **[G9.13]** Use animation of human figures to teach people how to make specific body movements by imitation.

It is also likely that mirror neurons can be the medium for motivating learners. If our brains mirror an enthusiastic person, this may make us more enthusiastic (see Figure 9.7). Certainly, energetic, exaggerated body gestures are common to many motivational speakers.

Figure 9.7 Mirror neurons may be the medium whereby one person motivates another. (*From http://www.honeysquad.com/index.php/tag/add-new-tag/. With permission.*)

Conclusion

Most complex visualizations used in explanations are hybrids of visual and verbal material. The message of this chapter is that information should be displayed in the most appropriate medium. Also, to obtain a positive benefit from multimedia presentations, cross-references must be made so that the words and images can be integrated conceptually. Both time and space can be used to create these cross-links. The deictic gesture, wherein someone points at an object while speaking about it, is probably the most elementary of visual–verbal linking devices. It is deeply embedded in human discourse and provides the cognitive foundation for other linking devices.

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CHAPTER TEN

Interacting with Visualizations

The kinds of interactions we discuss in this chapter are what Kirsh and Maglio (1994) called *epistemic* actions. An epistemic action is an activity intended to uncover new information. A good visualization is not just a static picture or a three-dimensional (3D) virtual environment that we can walk through and inspect like a museum full of statues. A good visualization is something that allows us to drill down and find more data about anything that seems important. Ben Shneiderman (1998) developed a mantra to guide visual information-seeking behavior and the interfaces that support it: "Overview first, zoom and filter, then details on demand." In reality, however, we are just as likely to see an interesting detail, zoom out to get an overview, find some related information in a lateral segue, and then zoom in again to get the details of the original object of interest. The important point is that a good computer-based visualization is an interface that can support all of these activities. Ideally, every data object on a screen will be active and not just a blob of color. It will be capable of displaying more information as needed, disappearing when not needed, and accepting user commands to help with the thinking processes.

Interactive visualization is a process made up of a number of interlocking feedback loops that fall into three broad classes. At the lowest level is the data manipulation loop, through which objects are selected and moved using the basic skills of eye–hand coordination. Delays of even a fraction of a second in this interaction cycle can seriously disrupt the performance of higher level tasks. At the intermediate level is an exploration and navigation loop, through which an analyst finds his or her way in a large visual data space. As people explore a new town, they build a cognitive spatial model using key landmarks and paths between them; something similar occurs when

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they explore data spaces. In the case of navigating data spaces, the time taken to get to a new vantage to find a particular piece of information is a direct *cost of knowledge*. Faster navigation means more efficient thinking. At the highest level is a problem-solving loop through which the analyst forms hypotheses about the data and refines them through an augmented visualization process. The process may be repeated through multiple visualization cycles as new data is added, the problem is reformulated, possible solutions are identified, and the visualization is revised or replaced. Sometimes the visualization may act as a critical externalization of the problem, forming a crucial extension of the cognitive process. This chapter deals with two of the three loops: low-level interaction and exploration. General problem solving is discussed in Chapter 11.

Data Selection and Manipulation Loop

A number of well established "laws" describe the simple, low-level control loops needed in tasks such as the visual control of hand position or the selection of an object on the screen.

Choice Reaction Time

Given an optimal state of readiness, with a finger poised over a button, a person can react to a simple visual signal in about 130 msec (Kohlberg, 1971). If the signals are very infrequent, the time can be considerably longer. Warrick et al. (1964) found reaction times as long as 700 msec under conditions where there could be as much as two days between signals. The participants were engaged in routine typing, so they were at least positioned appropriately to respond. If people are not positioned at workstations, their responses will naturally take longer.

Sometimes, one must make a choice before reacting to a signal. A simple choice-reaction-time task might involve pressing one button if a red light goes on and another if a green light goes on. This kind of task has been studied extensively. It has been discovered that reaction times can be modeled by a simple rule called the *Hick–Hyman law* for choice reaction time (Hyman, 1953). According to this law,

$$\text{Reaction time} = a + b\log_2(C) \tag{10.1}$$

where C is the number of choices, and a and b are empirically determined constants. The expression $\log_2(C)$ represents the amount of information processed by the human operator, expressed in bits of information.

Many factors have been found to affect choice reaction time—the distinctness of the signal, the amount of visual noise, stimulus–response compatibility, and so on—but under optimal conditions the response time per bit of information processed is about 160 msec, plus the time to set up the response. Thus, if there are eight choices (3 bits of information), the response time will typically be on the order of the simple reaction time plus approximately 480 msec. Another important factor is the degree of accuracy required. People respond faster if they are allowed to make mistakes occasionally, and this effect is called a *speed–accuracy tradeoff*. For a useful overview of factors involved in determining reaction time, see Card et al. (1983).

Two-Dimensional Positioning and Selection

In highly interactive visualization applications, it is useful to have graphical objects function not only as program output—a way of representing data—but also as program input—a way of finding out more about data. Selection using a mouse or similar input device (such as a joystick or trackball) is one of the most common interactive operations, and it has been extensively studied. A simple mathematical model provides a useful estimation of the time taken to select a target that has a particular position and size:

$$\text{Selection time} = a + b\log_2(D/W + 1.0) \tag{10.2}$$

where D is the distance to the center of the target, W is the width of the target, and a and b are constants determined empirically; see Figure 10.1(a). These are different for different devices.

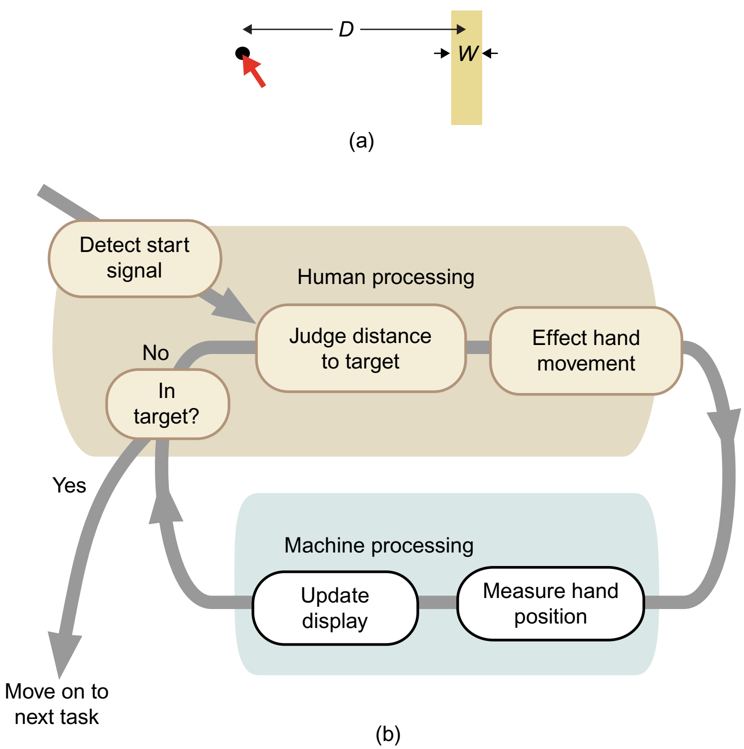


Figure 10.1 (a) A simplified reaching task, where the red cursor must be moved into the beige rectangle. (b) The visually guided reaching control loop, where the human processor makes adjustments based on visual feedback from the computer.

This formula is known as *Fitts' law*, after Paul Fitts (1954). The term $\log_2(D/W + 1.0)$ is known as the *index of difficulty* (ID). The value $1/b$ is the *index of performance* (IP) and is given in units of bits per second. There are a number of variations in the index-of-difficulty expression, but the one given here is the most robust (MacKenzie, 1992). Typical IP values for measured performance made with the fingertip, the wrist, and the forearm are all in the vicinity of 4 bits per second (Balakrishnan & MacKenzie, 1997). To put this into perspective, consider moving a cursor 16 cm across a screen to a 0.5-cm target. The index of difficulty will be about 5 bits. The selection will take more than a second longer than selecting a target that is already under the cursor.

Fitts' law can be thought of as describing an iterative process of eye–hand coordination, as illustrated in Figure 10.1(b). The human starts by judging the distance to the target and initiates the hand movement. On successive iterations, a corrective adjustment is made to the hand movement based on visual feedback showing the cursor position. Greater distances and smaller targets both result in more iterations. The logarithmic nature of the relationship derives from the fact that, on each iteration, the task difficulty is reduced in proportion to the remaining distance.

In many of the more complex data visualization systems, as well as in experimental data visualization systems using 3D virtual-reality (VR) technologies, there is a significant lag between a hand movement and the visual feedback provided on the display (Liang et al., 1991; Ware & Balakrishnan, 1994). Fitts' law, modified to include lag, looks like this:

$$\text{Mean time} = a + b(\mathit{HumanTime} + \mathit{MachineLag})\log_2(D/W + 1.0) \tag{10.3}$$

HumanTime is the human processing time and *MachineLag* is the time the computer takes to update the display based on user input. According to this equation, the effects of lag increase as the target gets smaller. Because of this, a fraction of a second lag can result in a subject taking several seconds longer to perform a simple selection task. This may not seem like much, but in a VR environment intended to make everything seem easy and natural, lag can make the simplest task difficult. Fitts' law is part of an International Standards Organization standard (ISO 9214-9) that sets out protocols for evaluating user performance and comfort when using pointing devices with visual display terminals. It is invaluable as a tool for evaluating potential new input devices.

Hover Queries

The most common kind of epistemic action with a computer is done by dragging a cursor over an object and clicking the mouse button. The *hover query* dispenses with the mouse click. Extra information is revealed about an object when the mouse cursor passes over it. Usually it is implemented with a delay; for example, the function of an icon is shown by a brief text message after hovering for a second or two. However, a hover query can function without a delay, making it a very rapid way of getting additional information. This enables the mouse cursor to be dragged over a set of data objects, quickly revealing the data contents and perhaps allowing an *interactive query rate* of several per second in special circumstances.

> **[G10.1]** For the fastest epistemic actions, use hover queries, activated whenever the mouse cursor passes over an object. These are only suitable where the query targets are dense and inadvertent queries will not be overly distracting.

Path Tracing

Fitts' law deals with single, discrete actions, such as reaching for an object. Other tasks, such as tracing a curve or steering a car, involve continuous ongoing control. In such tasks, we are continually making a series of corrections based on visual feedback about the results of our recent actions. Accot and Zhai (1997) made a prediction, based on Fitts' law, that applies to continuous steering tasks. Their derivation revealed that the speed at which tracing could be done should be a simple function of the width of the path:

$$v = W/\tau \tag{10.4}$$

where v is the velocity, W is the path width, and τ is a constant that depends on the motor control system of the person doing the tracing. In a series of experiments, the researchers found an almost perfect linear relationship between the speed of path following and the path width, confirming their theory. The actual values of τ lay between .05 and .11 sec, depending on the specific task. To make this more concrete, consider the problem of tracing a pencil along a 2-mm-wide path. Their results suggest that this will be done at a rate of between 1.8 and 4 cm/sec.

Two-Handed Interaction

In most computer interfaces, users select and move graphical objects around the screen with a mouse held in one hand, leaving the other hand unoccupied, but when interacting in the everyday world we frequently use both our hands. This leads us to the question of how we might improve the computer interface by taking advantage of both hands (Buxton & Myers, 1986).

The most important principle that has been discovered relating to the way tasks should be allocated to the two hands is Guiard's *kinematic chain theory* (Guiard, 1987). According to this theory, the left hand and the right hand form a kinematic chain, with the left hand providing a frame of reference for movements with the right, in right-handed individuals. For example, if we sculpt a small object out of modeling clay, we are likely to hold it in the left hand and do the detailed shaping with the right. The left hand reorients the piece and provides the best view, whereas the right pokes and prods within that frame of reference.

Interface designers have incorporated this principle into superior interfaces for various tasks (Bier et al., 1993; Kabbash et al., 1994). In an innovative computer-based drawing package, Kurtenbach et al. (1997) showed how templates, such as the French curve, could be moved rapidly over a drawing by a designer using his left hand while using his right hand to paint around the shape.

> **[G10.2]** When designing interfaces for two-handed data manipulations, the non-dominant hand (usually the left) should be used to control frame-of-reference information, while the dominant hand (usually the right) should be used to make detailed selections or manipulations of data.

Another beneficial use of the left hand is in positioning tools for easy access. In interactive drawing packages, users spend a lot of time moving between the drawing and various menus positioned off to the side of the screen. The *toolglass* and *magic lens* approach, developed by Bier et al. (1993), got around this problem by allowing users to use the left hand to position tool palettes and the right hand to do normal drawing operations. This allowed for very quick changes in color or brush characteristics. As an additional design refinement, they also made some of the tools transparent (hence toolglasses).

In an application more relevant to information visualization, Stone et al. (1994) developed the magic lens idea as a set of interactive information filters implemented as transparent windows that the user can move over an information visualization with the left hand. The magic lens can be programmed to be a kind of data X-ray, revealing normally invisible aspects of the data. Figure 10.2, for example, shows a map with land use patterns in the area around Charlotte, North Carolina (Butkiewicz et al., 2010). The magic lens reveals population density in the area it covers. A good interface for selections to be made based on population density would use the right hand, in a conventional way, to control a cursor to "click through" the magic lens, while the left hand would be used to position the lens.

Learning

Over time, people become more skilled at any task, barring fatigue, sickness, or injury. A simple expression known as the *power law of practice* describes the way task performance speeds up over time (Card et al., 1983):

$$\log(T_n) = C - \alpha \log(n) \tag{10.5}$$

where $C = \log(T_n)$ is based on the time to perform the task on the first trial, T_n is the time required to perform the nth trial, and α is a constant that represents the steepness of the learning curve. The implication of the log function is that it may take thousands of trials for a skilled person to improve his performance by 10% because he is far along

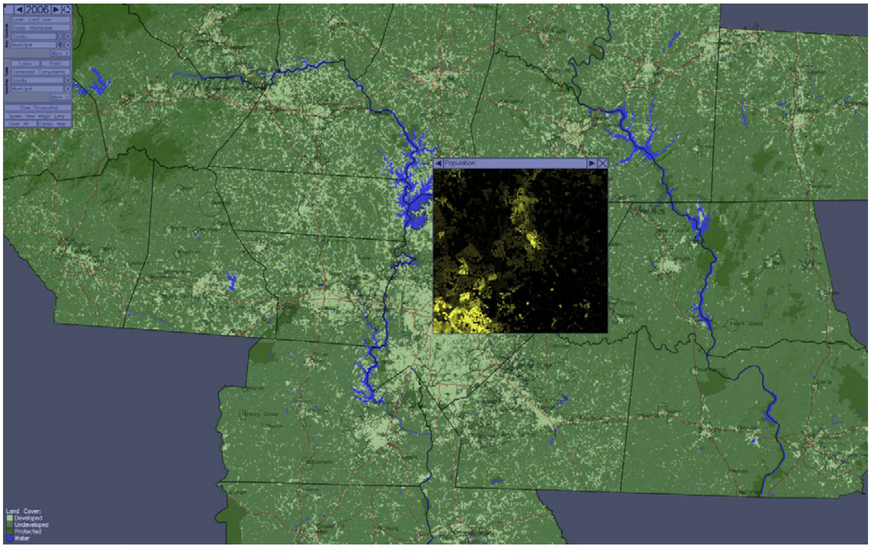


Figure 10.2 A magic lens showing population density with a background map showing land-use patterns. (*From Butkiewicz et al. (2010). Courtesy of Tom Butkiewicz.*)

the learning curve. In contrast, a novice may see a 10% gain after only one or two trials.

One of the ways in which skilled performance is obtained is through the chunking of small subtasks into programmed motor procedures. The beginning typist must make a conscious effort to hit the letters *t*, *h*, and *e* when typing the word *the*, but the brains of experienced typists can execute preprogrammed bursts of motor commands so that the entire word can be typed with a single mental command to the motor cortex. Skill learning is characterized by more and more of the task becoming automated and encapsulated. To encourage skill automation, the computer system should provide rapid and clear feedback of the consequences of user actions (Hammond, 1987).

Control Compatibility

Some control movements are easier to learn than others, and this depends heavily on prior experience. If you move a computer mouse to the right, causing an object on the screen to move to the right, this positioning method will be easy to learn. A skill is being applied that you gained very early in life when you first moved an object with your hand and that you have been refining ever since. But, if the system interface has been created such that a mouse movement to the right causes a graphical object to move to the left, this will be incompatible with everyday experience, and positioning the object will be difficult. In the behaviorist tradition of psychology, this factor is generally called *stimulus–response (S–R) compatibility*. In modern cognitive psychology, the effects of S-R compatibility are readily understood in terms of skill learning and skill transfer.

In general, it will be easier to execute tasks in computer interfaces if the interfaces are designed in such a way that they take advantage of previously learned ways of doing things. Nevertheless, some inconsistencies are easily tolerated, whereas others are not. For example, many user interfaces amplify the effect of a mouse movement so that a small hand movement results in a large cursor movement. Psychologists have conducted extensive experiments that involve changing the relationship between eye and hand. If a prism is used to laterally displace what is seen relative to what is felt, people can adapt in minutes or even seconds (Welch & Cohen, 1991). This is like using a mouse that is laterally displaced from the screen cursor being controlled. People are also able to adapt easily to relatively small inconsistencies between the angle of a hand movement and the angle of an object movement that results. For example, a 30-degree angular inconsistency is barely noticed (Ware & Arsenault, 2004).

On the other hand, if people are asked to view the world inverted with a mirror, it can take weeks of adaptation for them to learn to operate in an upside-down world (Harris, 1965). Snyder and Pronko (1952) had subjects wear inverting prisms continuously for a month. At the end of this period, reaching behaviors seemed error free, but the world still seemed upside down. This suggests that if we want to achieve good eye–hand coordination in an interface, we do not need to worry too much about matching hand translation with virtual object translation, but we should worry about large inconsistencies in the axis of rotation.

[G10.3] When designing interfaces to move objects on the screen, be sure that object movement is in the same general direction as hand movement.

Some imaginative interfaces designed for virtual reality involve extreme mismatches between the position of the virtual hand and the proprioceptive feedback from the user's body. In the Go-Go Gadget technique (named after the cartoon character Inspector Gadget), the user's virtual hand is stretched out far beyond his or her actual hand position to allow for manipulation of objects at a distance (Poupyrev et al., 1996).

Studies by Ramachandran (1999) provide interesting evidence that even under extreme distortions people may come to act as if a virtual hand is their own, particularly if touch is stimulated. In one of Ramachandran's experiments, he hid a subject's hand behind a barrier and showed the subject a grotesque rubber Halloween hand. Next, he stroked and patted the subject's actual hand and the Halloween hand in exact synchrony. Remarkably, in a very short time, the subject came to perceive that the Halloween hand was his or her own. The strength of this identification was demonstrated when the researcher hit the Halloween hand with a hammer. The subjects showed a strong spike in galvanic skin response (GSR), indicating a physical sense of shock. No shock was registered without the stroking. The important point from the perspective of VR interfaces is that even though the fake hand and the subject's real hand were in quite different places a strong sense of identification occurred.

Consistency with real-world actions is only one factor in skill learning. There are also the simple physical affordances of the task itself. It is easier for us to make certain body movements than others. Very often we can make computer-mediated tasks easier to perform than their real-world counterparts. When designing a house, we do not need to construct it virtually with bricks and concrete. The magic of computers is that a single button click can often accomplish as much as a prolonged series of actions in the real world. For this reason, it would be naive to conclude that computer interfaces should evolve toward VR simulations of real-world tasks or even enhanced Go-Go Gadget types of interactions.

Exploration and Navigation Loop

Viewpoint navigation is important in visualization when the data is mapped into an extended and detailed 3D space. Viewpoint navigation is cognitively complex, encompassing theories of path finding and map use, cognitive spatial metaphors, and issues related to direct manipulation and visual feedback.

Figure 10.3 sketches the basic navigation control loop. On the human side is a cognitive logical and spatial model whereby the user understands the data space and his or her progress through it. If the data space is maintained for an extended period, parts of its spatial model may become encoded in long-term memory. On the computer side, the view of the visualization is changed, based on user input.

We start with the problem of 3D locomotion; next we consider the problem of path finding and finally move on to the more abstract problem of maintaining focus and context in abstract data spaces.

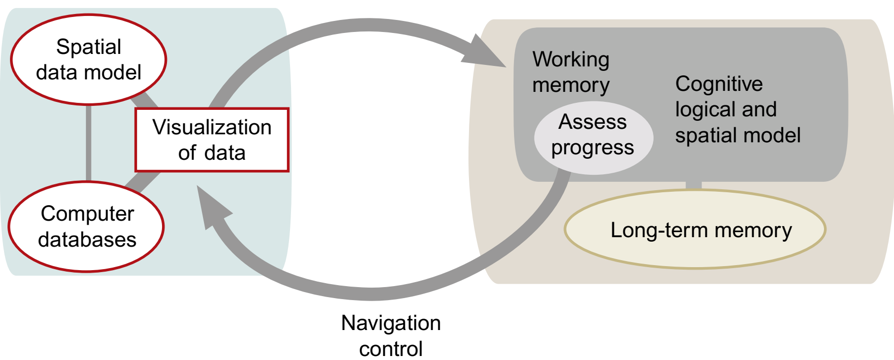


Figure 10.3 The navigation control loop.

Locomotion and Viewpoint Control

Some data visualization environments show information in such a way that it looks like a 3D landscape, not just a flat map. This is achieved with remote sensing data from other planets, as well as maps of the ocean floor and other data related to the terrestrial environment. The data landscape idea has also been applied to abstract data spaces such as the World Wide Web (see Figure 10.4 for an example). The idea is that we should find it easy to navigate through data presented in this way because we can harness our real-world spatial interpretation and navigation skills. James Gibson (1986) offered an environmental perspective on the problem of perceiving for navigation:

> *A path affords pedestrian locomotion from one place to another, between the terrain features that prevent locomotion. The preventers of locomotion consist of obstacles, barriers, water margins and brinks (the edges of cliffs). A path must afford footing; it must be relatively free of rigid foot-sized obstacles.*

Gibson described the characteristics of obstacles, margins, brinks, steps, and slopes. According to Gibson, locomotion is largely about perceiving and using the affordances offered for navigation by the environment. (See Chapter 1 for a discussion of affordances.) His perspective can be used in a quite straightforward way in designing virtual environments, much as we might design a public museum or a theme park. The designer creates barriers and paths in order to encourage visits to certain locations and discourage others.

We can also understand navigation in terms of the depth cues presented in Chapter 7. All the perspective cues are important in providing a sense of scale and distance, although the stereoscopic cue is important only for close-up navigation in situations

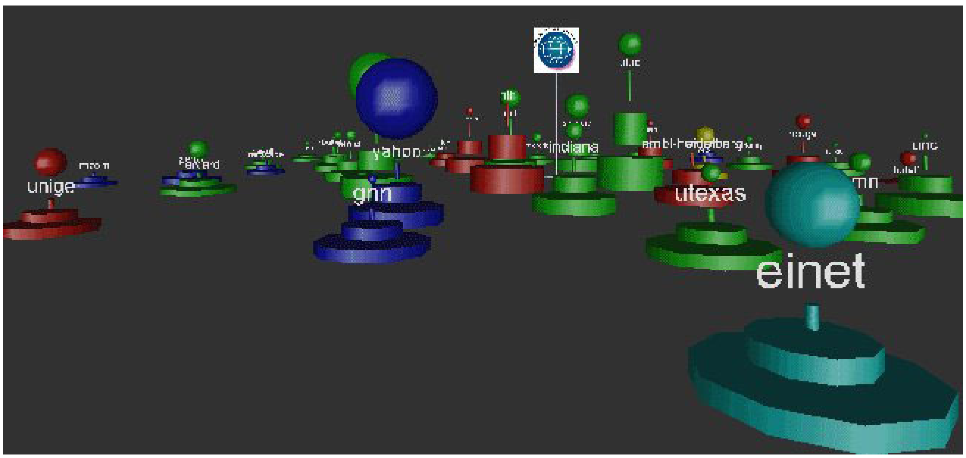


Figure 10.4 Websites arranged as a data landscape. (*From* Bray (1996). *Reproduced with permission*.)

such as walking through a crowd. When we are navigating at higher speeds, in an automobile or a plane, stereoscopic depth is irrelevant, because the important parts of the landscape are beyond the range of stereoscopic discrimination. Under these conditions, structure-from-motion cues and information based on perceived objects of known size are critical.

It is usually assumed that a smooth motion flow of visual texture across the retina is necessary for judgment of the direction of self-motion within the environment. But Vishton and Cutting (1995) investigated this problem using VR technology, with subjects moving through a forest-like virtual environment, and concluded that relative displacement of identifiable objects over time was the key, not smooth motion. Their subjects could do almost as well with a low frame rate, with images presented only 1.67 times per second, but performance declined markedly when updates were less than 1 per second. The lesson for the design of virtual navigation aids is that these environments should be sparsely populated with a sufficient number of objects to provide frame-to-frame cues about self-motion.

> **[G10.4]** To support view navigation in 3D data spaces, a sufficient number of objects must be visible at any time to judge relative view position, and several objects must persist from one frame to the next to maintain continuity.

Ideally, frame rates should be at least 2 per second; however, although judgments of heading may not be impaired by low frame rates, other problems will result. Low frame rates cause lag in visual feedback and, as discussed previously, this can introduce serious performance problems.

Changing the viewpoint in a data space can be done using a navigation metaphor, such as walking or flying, or it can be done using a more abstract, nonmetaphoric style of interaction, such as zooming in to a selected point on a data object. Ultimately, the goal is to get to the most informative view of the data space efficiently. The use of metaphors may make learning the user interface easier, but a nonmetaphoric interaction method may ultimately be the best.

Spatial Navigation Metaphors

Interaction metaphors are cognitive models for interaction that can profoundly influence the design of interfaces to data spaces. Here are two sets of instructions for different viewpoint control interfaces:

1. "Imagine that the model environment shown on the screen is like a real model mounted on a special turntable that you can grasp, rotate with your hand, move sideways, or pull towards you."
2. "Imagine that you are flying a helicopter and its controls enable you to move up and down, forward and back, left and right."

With the first interface metaphor, if the user wishes to look at the right side of the scene, she must rotate the scene to the left to get the correct view. With the second interface metaphor, the user must fly her vehicle forward and around to the right, while turning in toward the target. Although the underlying geometry in the two cases is the same, the user interface and the user's conception of the task are very different.

Navigation metaphors have two fundamentally different kinds of constraints on their usefulness. The first of these constraints is essentially cognitive. The metaphor provides the user with a model that enables the prediction of system behavior given different kinds of input actions. A good metaphor is one that is apt, matches the system well, and is easy to understand. The second constraint is more of a physical limitation. The implementation of a particular metaphor will naturally make some actions physically easy to carry out and others difficult to carry out; for example, a walking metaphor limits the viewpoint to a few feet above ground level and the speed to a few meters per second. Both kinds of constraints are related to Gibson's concept of affordances—a particular interface affords certain kinds of movement and not others, but it must also be perceived to embody those affordances.

Note that, as discussed in Chapter 1, we are going beyond Gibson's view of affordances here. Gibsonian affordances are directly perceived properties of the physical environment. In computer interfaces interaction is indirect, mediated through the computer, and so is perception of data objects, so Gibson's concept as he framed it does not strictly apply. We must extend the notion of affordances to apply to both the physical constraints imposed by the user interface and cognitive constraints relating to the user's understanding of the data space. A more useful definition of an interface with good cognitive affordances is one that makes the possibility for action plain to the user and gives feedback that is easy to interpret.

Four main classes of metaphors have been employed in the problem of controlling the viewpoint in virtual 3D spaces. Figure 10.5 provides an illustration and summary. Each metaphor has a different set of affordances.

> ***World-in-hand.*** The user metaphorically grabs a part of the 3D environment and moves it (Ware & Osborne, 1990; Houde, 1992). Moving the viewpoint closer to a point in the environment actually involves pulling the environment closer to the user. Rotating the environment similarly involves twisting the world about a point as if it were held in the user's hand. A variation on this metaphor has the object mounted on a virtual turntable or gimbal. The world-in-hand model would seem to be optimal for viewing discrete, relatively compact data objects, such as virtual vases or telephones. It does not provide affordances for navigating long distances over extended terrains.

> ***Eyeball-in-hand.*** In the eyeball-in-hand metaphor, the user imagines that she is directly manipulating her viewpoint, much as she might control a camera by

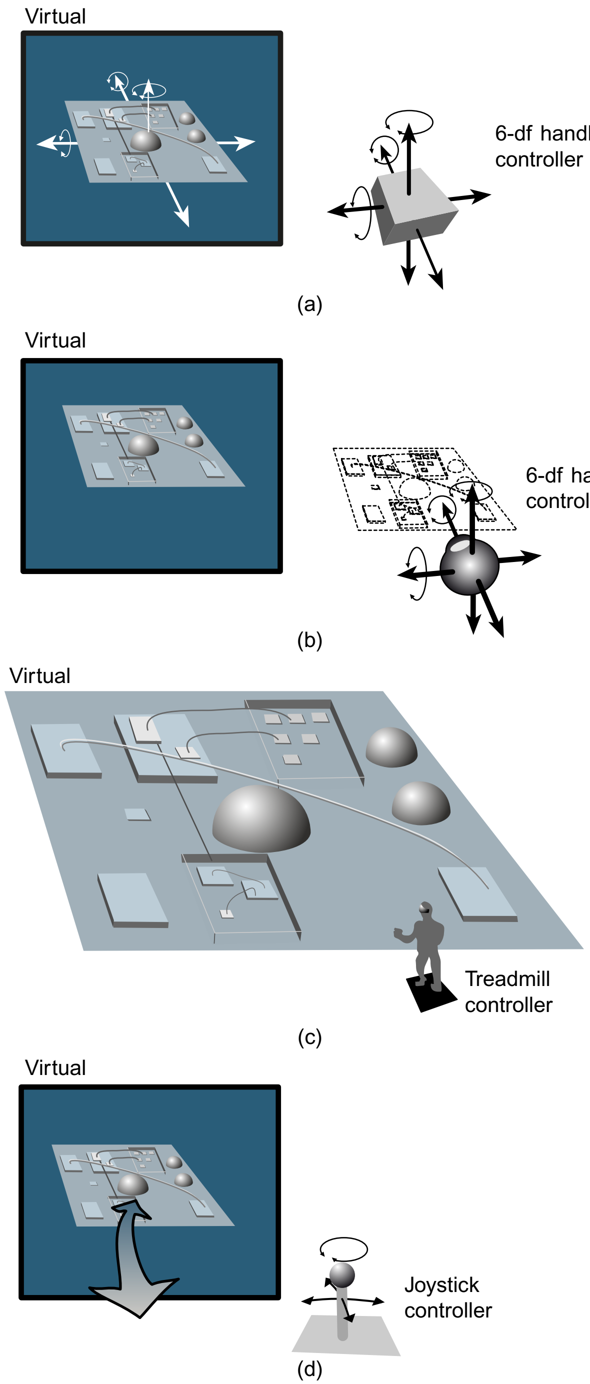


Figure 10.5 Four navigation metaphors: (a) World-in-hand. (b) Eyeball-in-hand. (c) Walking. (d) Flying.

pointing it and positioning it with respect to an imaginary landscape. The resulting view is represented on the computer screen. This is one of the least effective methods for controlling the viewpoint. Badler et al. (1986) observed that "consciously calculated activity" was involved in setting a viewpoint. Ware and Osborne (1990) found that some viewpoints were easy to achieve but others led to considerable confusion. They also noted that with this technique physical affordances are limited by the positions in which the user can physically place her hand. Certain views from far above or below cannot be achieved or are blocked by the physical objects in the room.

Walking. One way of allowing inhabitants of a virtual environment to navigate is to simply let them walk. Unfortunately, even though a large extended virtual environment can be created, the user will soon run into the real walls of the room in which the equipment is housed. Most VR systems require a handler to prevent the inhabitant of the virtual world from tripping over the real furniture. A number of researchers have experimented with devices such as exercise treadmills so that people can walk without actually moving over the ground. Typically, something like a pair of handlebars is used to steer. In an alternative approach, Slater et al. (1995) created a system that captures the characteristic up-and-down head motion that occurs when people walk in place. When this head bobbing is detected, the system moves the virtual viewpoint forward in the direction of head orientation. This gets around the problem of bumping into walls and may be useful for navigating in environments such as virtual museums; however, the affordances are still restrictive.

Flying. Modern digital terrain visualization packages commonly have fly-through interfaces that enable users to smoothly create an animated sequence of views of the environment. Some of these are quite literal, having aircraft-like controls. Others use the flight metaphor only as a starting point. No attempt is made to model actual flight dynamics; rather, the goal is to make it easy for the user to get around in 3D space in a relatively unconstrained way. We (Ware & Osborne, 1990) developed a flying interface that used simple hand motions to control velocity. Unlike real aircraft, this interface makes it as easy to move up, down, or backward as it is to move forward. Subjects with actual flying experience had the most difficulty; because of their expectations about flight dynamics, pilots did unnecessary things such as banking on turns and were uncomfortable with stopping or moving backward. Subjects without flying experience were able to pick up the interface more quickly. Despite its lack of realism, this was rated as the most flexible and useful interface when compared to others based on the world-in-hand and eyeball-in-hand metaphors. It later became the original user interface for Fledermaus™, a 3D geospatial visualization package.

The optimal navigation method depends on the exact nature of the task. A virtual walking interface may be the best way to give a visitor a sense of presence in an architectural space. Something loosely based on the flying metaphor may be a more useful way of navigating through spatially extended data landscapes. The affordances of the virtual data space, the real physical space, and the input device all interact with the mental model of the task that the user has constructed.

Wayfinding, Cognitive Maps, and Real Maps

In addition to the problem of moving through an environment in real time, there is the meta-level problem of how people build an understanding of larger environments over time and how they use this understanding to seek information. One aspect of this problem is usually called *wayfinding*. It encompasses both the way in which people build mental models of extended spatial environments and the way they use physical maps as aids to navigation.

Unfortunately, this area of research is plagued with a diversity of terminology. Throughout the following discussion, bear in mind that there are two clusters of concepts, and the differences between these clusters relate to the dual-coding theory discussed in Chapter 9. One cluster includes the related concepts of *declarative knowledge*, *procedural knowledge*, *topological knowledge*, and *categorical representations*. These concepts are fundamentally logical and nonspatial and therefore mostly nonvisual. The other cluster includes the related concepts *of spatial cognitive maps* and *coordinate representations*. These are fundamentally spatial.

Seigel and White (1975) proposed that there are three stages in the formation of wayfinding knowledge. First, information about key landmarks is learned; initially, there is no spatial understanding of the relationships between them. This is sometimes called *declarative knowledge*. We might learn to identify a post office, a church, and the hospital in a small town.

Second, procedural knowledge about routes from one location to another is developed. Landmarks function as decision points. Verbal instructions often consist of procedural statements related to landmarks, such as, "Turn left at the church, go three blocks, and turn right by the gas station." This kind of information also contains topological knowledge, because it includes connecting links between locations. Topological knowledge has no explicit representation of the spatial position of one landmark relative to another.

Third, a cognitive spatial map is formed. This is a representation of space that is two dimensional and includes quantitative information about the distances between the different locations of interest. With a cognitive spatial map, it is possible to estimate the distance between any two points, even though we have not traveled directly between them, and to make statements such as, "The university is about one kilometer northwest of the train station." In Seigel and White's initial theory and in much of the subsequent work, there has been a presumption that spatial knowledge developed strictly in the order of these three stages: declarative knowledge, procedural knowledge, and cognitive spatial maps.

Seigel and White's theory, however, ignored the importance of map technologies. Cognitive maps can be acquired directly from an actual map much more rapidly than by traversing the terrain. Thorndyke and Hayes-Roth (1982) compared people's ability to judge distances between locations in a large building. Half of them had studied a map for half an hour or so, whereas the other half never saw a map but had worked in the building for many months. The results showed that for estimating the straight-line Euclidean distance between two points, a brief experience with a map was equivalent to working in the building for about a year. For estimating the distance along the hallways, however, the people with experience in the building did the best.

People can easily construct spatial mental maps of the objects they can see together from a particular vantage point. Colle and Reid (1998) conducted an experimental study using a virtual building consisting of a number of rooms connected by corridors. The rooms contained various objects. In a memory task following the exploration of the building, subjects were found to be very poor at indicating the relative positions of objects located in different rooms, but they were good at indicating the relative positions of objects within the same room. This suggests that cognitive spatial maps form easily and rapidly in environments where the viewer can see everything at once, as is the case for objects within a single room. It is more likely that the paths from room to room were captured as procedural knowledge. The practical application of this is that overviews should be provided wherever possible in extended spatial information spaces.

[G10.5] Consider providing an overview map to speed up the acquisition of a mental map of a data space.

[G10.6] Consider providing a small overview map to support navigation through a large data space.

Perspective views are less effective in supporting the generation of mental maps. Darken et al. (1998) reported that Navy pilots typically fail to recognize landmark terrain features on a return path, even if these were identified correctly on the outgoing leg of a low-flying exercise. This suggests that terrain features are not encoded in memory as fully three-dimensional structures, but rather are remembered in some viewpoint-dependent fashion as predicted by the image-based theory of object recognition discussed in Chapter 8.

The results of Colle and Reid's study fit well with a somewhat different theory of spatial knowledge proposed by Kosslyn (1987). He suggested that there are only two kinds of knowledge, not necessarily acquired in a particular order. He called them *categorical* and *coordinate* representations. For Kosslyn, categorical information is a combination of both declarative knowledge and topological knowledge, such as the identities of landmarks and the paths between them. Coordinate representation is like the cognitive spatial map proposed by Seigel. A spatial coordinate representation would be expected to arise from the visual imagery obtained with an overview. Conversely, if knowledge were constructed from a sequence of turns along corridors when the subject was moving from room to room, the natural format would be categorical.

Landmarks, Borders, and Place

In an influential paper in the field of city planning, Lynch (1960) classified the structure of a city in terms of regions where different kinds of activities took place, boundaries blocking locomotion, landmarks providing focus points and aids to navigation, and pathways affording navigation. Recent work in neuroscience has shown remarkable parallels between at least some of these structures and processes operating in a mid-brain structure called the *hippocampus*, a region of the brain that has long been known to be important for our understanding of space (O'Keefe & Nadel, 1978). Three types of neurons have been identified: *Border cells* signal impenetrable barriers, *place cells* signal specific locations (e.g., at the fridge, by the stove, on the sofa in the living room) (Solstad et al., 2008), and *grid cells* contain an updated map of where we are currently, relative to our surroundings (Hafting et al., 2005). These contain links to place cell and object cell information.

All of this suggests that visual landmarks representing meaningful data objects are important in visualization design. Landmarks can tie points between declarative or procedural representations in the mind, with spatial representations provided in an external map. Vinson (1999) created a set of design guidelines for landmarks in virtual environments. The following guidelines can be added to G10.4:

> **[G10.7]** When designing a set of landmarks, make each landmark visually distinct from the others.

> **[G10.8]** When designing a landmark, make it recognizable as far as possible at all navigable scales.

Creating recognizable landmarks in 3D environments can be difficult because of multiple viewpoints. As discussed in Chapter 8, we recognize objects better from familiar and canonical viewpoints. An interesting way to assist users to encode landmarks for navigation in 3D environments was developed by Elvins et al. (1997). They presented subjects with small 3D subparts of a virtual cityscape that they called *worldlets*. The worldlets provided 3D views of key landmarks, presented in such a way that observers could rotate them to obtain a variety of views. Subsequently, when they were tested in a navigation task, subjects who had been shown the worldlets performed significantly better than subjects who had been given pictures of the landmarks or subjects who had simply been given verbal instructions.

Frames of Reference

The ability to generate and use something cognitively analogous to a map can be thought of in terms of applying a different perspective or frame of reference to the world. A map is like a view from a viewpoint high in the sky. Cognitive frames of reference are often classified into *egocentric* and *exocentric*. According to this classification, a map is just one of many exocentric views—views that originate outside of the user.

Egocentric Frame of Reference

The egocentric frame of reference is, roughly speaking, our subjective view of the world. It is anchored to the head or torso, not the direction of gaze (Bremmer et al., 2001). Our sense of what is ahead, left, and right does not change as we move our eyes around the scene, but it does change with body and head orientation. As we explore the world, we change our egocentric viewpoint primarily around two, not three, axes of rotation. As illustrated in Figure 10.6 we turn our bodies mostly around a vertical axis (pan) to change heading, and swivel our heads on the neck (also pan) about a similar vertical axis for more rapid adjustments in view direction. We also tilt our heads forward and back but generally not to the side (roll). The same two axes are represented in eye movements; our eyeballs do not rotate about the axis of the line of sight. More concisely, human angle of view control normally has only two degrees of freedom (pan and tilt) and lacks roll.

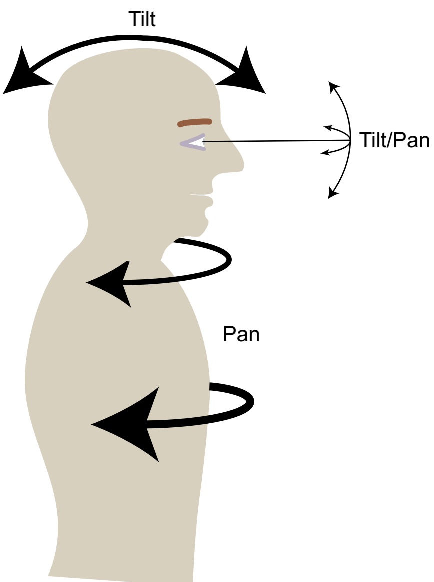


Figure 10.6 Most of the time we only rotate our viewpoint about two axes, corresponding to tilt and pan.

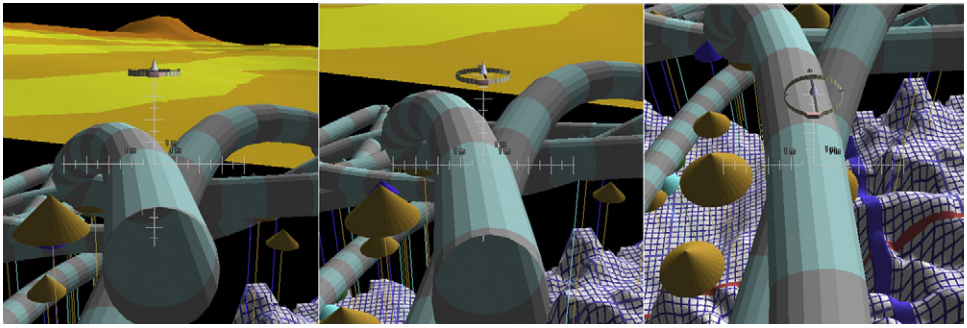


Figure 10.7 View control widgets for examining geographic data. Note that the rotational degrees of freedom match the rotational degrees of freedom of egocentric coordinates. The three views show different amounts of tilt. The handle on the top widgets can be dragged up and down to change tilt and moved left and right to rotate about the vertical axis.

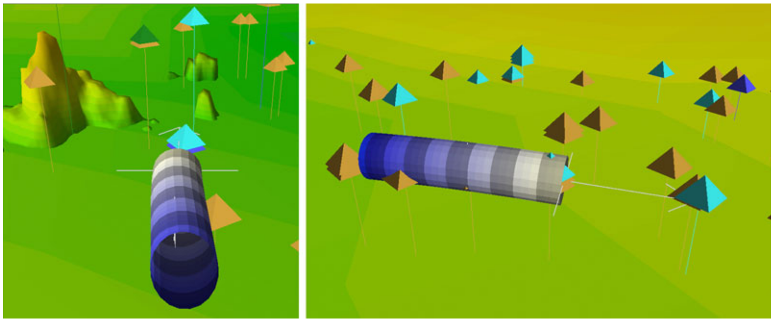
A consequence of the fact that we are most familiar with only two of the three degrees of freedom of viewpoint rotation is that when viewing maps, either real or in a virtual environment, we are most comfortable with only two degrees of freedom of rotation. Figure 10.7 illustrates an interface for rotating geographical information spaces constructed to have the same two degrees of freedom (Ware et al., 2001). The widgets allow rotation around the center point (equivalent to turning the body) and tilt from horizontal up into the plane of the screen (equivalent to forward and back head tilt), but they do not allow rotation around the line of site through the center of the screen (equivalent to the rarely used sideways head tilt).

> **[G10.9]** In interfaces to view map data in 3D, the default controls should allow for tilt around a horizontal axis and rotation about a vertical axis, but not rotation around the line of sight.

Because we tend to move our bodies forward and only rarely sideways, a simple interface to simulate human navigation can be constructed with only three degrees of freedom, two for rotations (heading and tilt) and one to control forward motion in the direction of heading. If a fourth degree of freedom is added, it may be most useful to allow for something analogous to head turning. This allows for sideways glances while traveling forward.

Exocentric Frames of Reference

The term *exocentric* simply means external. In 3D computer graphics, exocentric frames of reference are used for applications such as monitoring avatars in video games, controlling virtual cameras in cinematography, and monitoring the activities of remote or



(a) (b)

Figure 10.8 (a) God's-eye view of a moving vehicle represented by the tube object in the foreground. (b) Wingman's view of the same vehicle.

autonomous vehicles. Obviously, there is an infinite number of exocentric views. The following is a list of some of the more important and useful ones:

- ***Another person's view.*** For some tasks, it can be useful to take the egocentric view of someone else who is already present in our field of view. Depending on the angular disparity in the relative directions of gaze, this can be confusing, especially when the other person is facing us. In the *ClearBoard* system (Ishii & Kobayashi, 1992), a remote collaborator appeared to be writing on the other side of a pane of glass. By digitally reversing the image, a common left–right frame of reference was maintained.
- ***Over the shoulder view.*** A view from just behind and to the side of the head of an individual. This view is commonly used in cinematography.
- ***God's-eye view.*** Following a vehicle or avatar from above and behind, as shown in Figure 10.8(a). This view is very common in video games. Because it provides a wider field of view, it can be better for steering a remote vehicle than the more obvious choice, an egocentric view from the vehicle itself (Wang & Milgram, 2001).
- ***Wingman's view.*** Following a vehicle or avatar while looking at it from the side, as shown in Figure 10.8(b). Exocentric views that follow a moving object, such as the God's-eye or wingman's views, are sometimes called *tethered* (Wang & Milgram, 2001).

Map Orientation

Three views are commonly available in electronic map and chart displays:

- ***North-up plan view.*** This is the classic orthographic map view, with north up, usually with the vehicle placed in the middle, oriented appropriately.
- ***Track-up plan view.*** Also an orthographic map view, but oriented so that the heading of the vehicle is in the vertical up direction on the map.

- ***Track-up-perspective view.*** This is another name for the God's-eye view already mentioned. In this case, the map is given a perspective view on the screen. The viewpoint is above and behind the vehicle.

The first two of these are illustrated in Figure 10.9(a, b) and the third in Figure 10.9(c).

A number of studies have compared north-up plan views with track-up views and suggested that the track-up view is preferable in that it is easier to use and results in fewer errors (Levine et al., 1984; Shepard & Hurwitz, 1984; Aretz, 1991). Nevertheless, experienced navigators often prefer the north-up over the track-up view because it gives them a consistent frame of reference for interpreting geographic data. This is especially important when two map interpreters are communicating over a phone or radio link—for example, in battlefield situations or when scientists are collaborating at a distance.

In visual cognitive terms, using a map involves comparing imagery on a display with objects in the world. This can be conceptualized as creating a cognitive binding between visual objects visible in two different spatial reference frames. In his work on displays for pilots, Aretz (1991) identified two different mental rotations necessary for successful map use. The first, azimuthal rotation, is used to align a map with the direction of travel. The track-up display executes this rotation in the display computer,

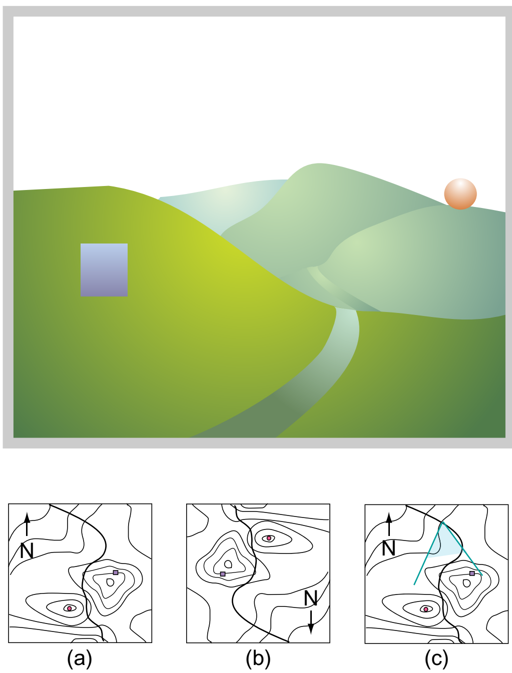


Figure 10.9 (a) North-up map. (b) Track-up map. (c) North-up map with user view explicitly displayed.

eliminating the need for the task to be performed mentally. The second is vertical tilt. A map can be horizontal, in which case it directly matches the plane of the displayed information, or it can be oriented vertically, as is typical of the map displays used in car dashboards. Of these two transformations, azimuthal misalignment is the one that gives the most cognitive difficulty, and its difficulty increases in a nonlinear fashion. People take much longer and are less accurate when a map is aligned more than 90 degrees from their direction of travel (Wickens, 1999; Gugerty & Brooks, 2001).

It is possible to enhance a north-up map and make it almost as effective as a track-up map, even for novices. Aretz (1991) evaluated a north-up map with the addition of a clear indicator of the forward field of view of the navigator. This significantly enhanced the ability of the users to orient themselves. Figure 10.9(c) illustrates this kind of enhanced map.

> **[G10.10]** When designing an overview map, provide a "you are here" indicator that shows location and orientation.

Tilting a display to form an oblique track-up-perspective view (God's-eye) is less disruptive of performance than azimuthal misalignment (Hickox & Wickens, 1999). This may be at least partly because the misalignment in tilt is never more than 90 degrees and often much less. A perspective track-up view (like the top panel of Figure 10.9) reduces the tilt mismatch between the display and the environment or can entirely eliminate it if the view exactly matches the world view of the user, in which case we have an egocentric view. But, one of the problems with the egocentric view is that the user cannot see very far ahead, especially if a 3D scene is rendered with buildings and landscape features obscuring the view.

Track-up-perspective views have been studied for application in the field of aviation human factors (Schreiber et al., 1998; Hickox & Wickens, 1999). These studies show that the relative tilt angle between the display perspective and the scene perspective has a significant effect only if the angles are relatively large. Mismatches of 20 degrees or less resulted in minimal or no disruption of performance.

> **[G10.11]** Maps used in navigation should provide three views: north-up, track-up, and track-up-perspective. A track-up perspective view should be the default.

Focus, Context, and Scale in Nonmetaphoric Interfaces

We have been dealing with the problem of how people navigate through 3D data spaces, under the assumption that the methods used should reflect the way we navigate in the real world. The various navigation metaphors are all based on this assumption; however, several successful spatial navigation techniques do not use an explicit interaction metaphor but do involve visual spatial maps. These techniques make it easy to move quickly from one view to another at different scales; because of this, they are said to solve the *focus-context* problem. Think of the problem of wayfinding as one of discovering specific objects or detailed patterns (focus) in a larger data landscape (context). The focus–context problem is simply a generalization of this, the problem of finding detail in a larger context.

In a way, the terms *focus* and *context* are misleading. It implies that the small scale is the more important subject of attention, but in data analysis important patterns can occur at any spatial scale. The important thing is to be able to easily relate large-scale patterns to small-scale patterns. We will not abandon the focus and context terms, though, because they are too deeply entrenched.

The three kinds of focus–context problems are concerned with the spatial properties, structural properties, or temporal properties of a data set. Sometimes all three can be involved.

- ***Spatial scale.*** Spatial-scale problems are common to all mapping applications; for example, a marine biologist might want to understand the spatial behavior of individual codfish within a particular school off the Grand Banks of Newfoundland. This information is understood in the context of the shape of the continental shelf, as well as the boundary between cold Arctic water and the warm waters of the Gulf Stream.
- ***Structural scale.*** Complex systems can have structural components at many levels. A prime example is computer software. This has structure within a single line of code, structure within a subroutine or procedure (perhaps 50 lines of code), structure at the object level for object-oriented code (perhaps 1000 lines of code), and structure at the system level. Suppose that we want to visualize the structure of a large program, such as a digital telephone switch (comprising as many as 20 million lines of code); we may wish to understand its structure through as many as six levels of detail.
- ***Temporal scale.*** Many data visualization problems involve understanding the timing of events at very different scales. In understanding data communications, for example, it can be useful to know the overall traffic patterns in a network as they vary over the course of a day. It can also be useful to follow the path of an individual packet of information through a switch over the course of a few microseconds.

It is worth noting that the focus-context problem has already been spatially solved by the human visual system, at least for moderate changes in scale. The brain continuously integrates detailed information from successive fixations of the fovea with the less-detailed information that is available at the periphery. This is combined with data coming from the prior sequence of fixations. For each new fixation, the brain must somehow match key objects in the previous view with those same objects moved to new locations. Differing levels of detail are supported in normal perception because objects are seen at much lower resolution at the periphery of vision than in the fovea. The fact that we have no difficulty in recognizing objects at different distances means that scale-invariance operations are supported in normal perception. The best solutions to the problem of providing focus and context in a display are likely to take advantage of these perceptual capabilities.

The spatial scale of maps, the structural levels of detail in computer programs, and the temporal scale in communications monitoring are very different application domains, but they belong to a class of related visualization problems and they can all be *represented* by means of spatial layouts of data. The same interactive techniques can often be applied. In the following sections, we consider the perceptual properties of four different visualization techniques to solve the focus-context problem: distortion, rapid zooming, elision, and multiple windows.

Distortion Techniques

A number of techniques have been developed that spatially distort a data representation, giving more room to designated points of interest and decreasing the space given to regions away from those points. What is of immediate interest is spatially expanded at the expense of what is not, thus providing both focus and context. Some techniques have been designed to work with a single focus, such as the hyperbolic tree browser (Lamping et al., 1995), as shown in Figure 10.10.

An obvious perceptual issue related to the use of distorting focus–context methods is whether the distortion makes it difficult to identify important parts of the structure. This problem can be especially acute when actual geographical maps are expanded. For example, Figure 10.11, from Keahey (1998), shows a distorted map of the Washington, D.C., subway system. The center is clear as intended, but the labels on the stations surrounding the center have been rendered unintelligible. This leads to the next guideline.

> **[G10.12]** When designing a visualization that uses geometric fisheye distortion methods, allow a maximum scale change factor of five.

Some methods allow multiple foci to be simultaneously expanded, such as the *table lens* (Rao & Card, 1994) illustrated in Figure 10.12. Many of these methods use simple algebraic functions to distort space based on the distance from each focus.

The basic perceptual problem that can occur with distortion techniques is that parts of the structure will no longer be recognized. Distorting layout algorithms sometimes move parts of an information structure to radically different locations in the display space. This, of course, entirely defeats the purpose of focus and context, which

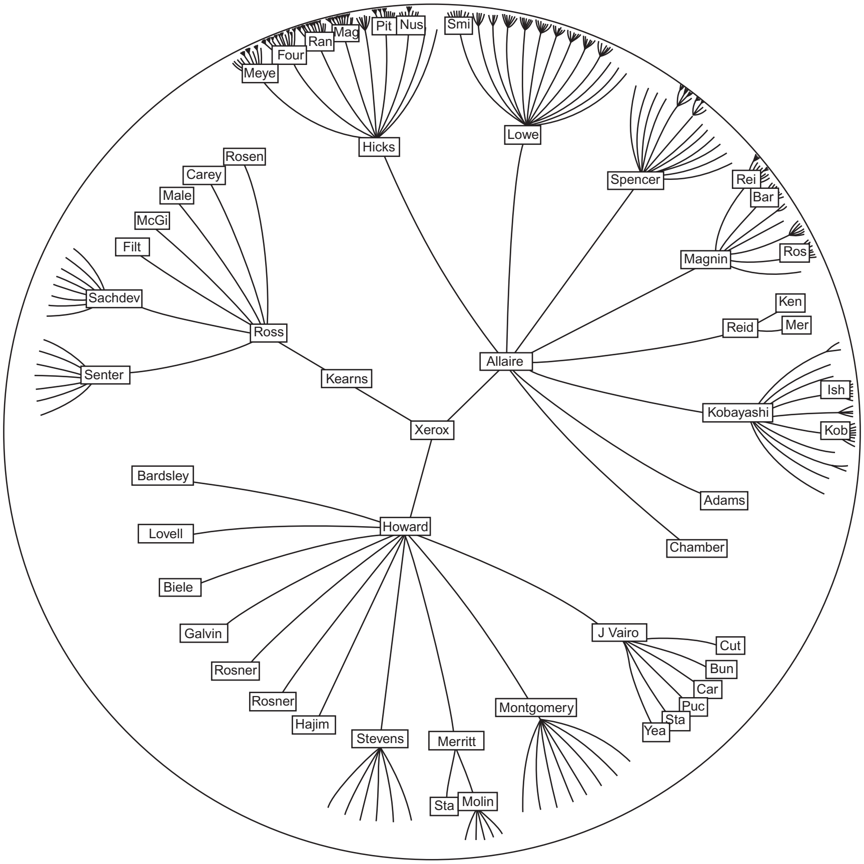


Figure 10.10 Hyperbolic tree browser from Lamping et al. (1995). The focus can be changed by dragging a node from the periphery to the center.

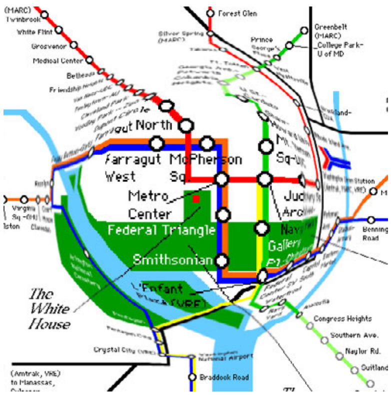


Figure 10.11 A fisheye view centered on downtown Washington, D.C. (*From* Keahey *(1998). Reproduced with permission.*)

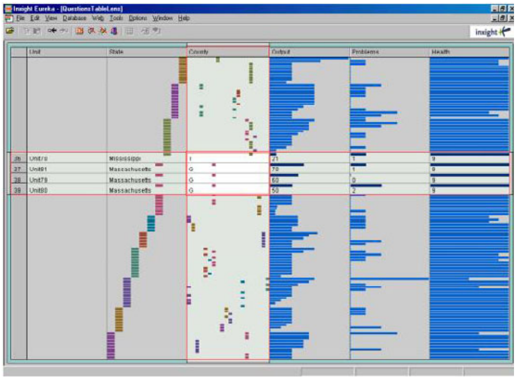


Figure 10.12 Table lens form Rao and Card (1994). Multiple row- and column-wise centers of focus can be created.

depends on memory of patterns to relate information represented at different spatial scales.

> **[G10.13]** Design fisheye distortion methods so that meaningful patterns are always recognizable.

Rapid Zooming Techniques

Another way of enabling people to comprehend focus and context is to use a single window but make it possible to transition quickly between spatial scales. Rapid zooming techniques do this. A large information landscape is provided, although only a part of it is visible in the viewing window at any instant. The user is given the ability to zoom rapidly into and out of points of interest, which means that, although focus and context are not simultaneously available, the user can move quickly and smoothly from focus to context and back. If smooth scaling is used, the viewer can perceptually integrate the information over time. The Pad and Pad++ systems (Bederson & Hollan, 1994) are based on this principle. They provide a large planar data landscape, with an interface using a simple point-and-click technique to move quickly and smoothly in and out.

The proper rate of zoom has been a subject of study (Guo et al., 2000; Plumlee, 2004). Plumlee's (2004) results suggest that the rate of zoom should be independent of the number of objects displayed and the frame rate but individual preferences vary widely. Some people prefer a zoom rate as slow as 2× per second, while others prefer a rate as fast as 8× per second (a zoom rate of 8× per second means that the scale is changing smoothly by a factor of 8 every second). Both studies suggest a default zoom rate of 3 to 4× per second.

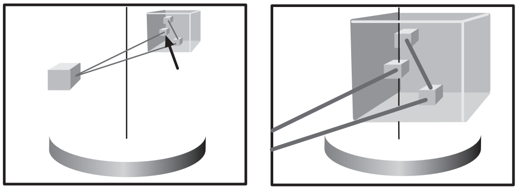


Figure 10.13 Center of workspace navigation. Clicking and dragging down on the box shown on the left causes it to move to the center of the workspace and expands the space around that center. Dragging up shrinks the space.

[G10.14] When designing a zooming interface, set a default scaling rate of 3 to 4× (magnification or minification) per second. The rate should be user changeable so that experts can increase it.

Mackinlay et al. (1990) invented a rapid navigation technique for 3D scenes that they called *point of interest* navigation. This method moves the user's viewpoint rapidly, but smoothly, to a point of interest that has been selected on the surface of an object. At the same time, the view direction is smoothly adjusted to be perpendicular to the surface. A variant of this is to relate the navigation focus to an object. Parker et al. (1998) developed a similar technique that is object based rather than surface based; clicking on an object scales the entire 3D virtual environment about the center of that object while simultaneously bringing it to the *center of the workspace*. This method is illustrated in Figure 10.13.

In all these systems, a key issue is the rapidity and ease with which the view can be changed from a focal one to an overview and back. Less than a second of transition time is probably a good rule of thumb, but the animation must be smooth to maintain the identity of objects in their contexts. To maintain a sense of location, landmark features should be designed to be recognized consistently, despite large changes in scale.

Elision Techniques

In visual *elision*, parts of a structure are hidden until they are needed. Typically, this is achieved by collapsing a large graphical structure into a single graphical object. It can be thought of as a kind of structural fisheye, also referred to as *semantic zoom* (Furnas, 1986). This is an essential component of the intelligent zoom system (Bartram et al., 1994), discussed in Chapter 11, and is becoming increasingly common in network visualizations. In these systems, when a node is opened it expands to reveal its contents. The success of structural methods depends on the extent to which related information can be naturally grouped into larger objects. Also, if the goal is to compare information that resides in little boxes, there must be a clear way of finding out something about what a box might reveal from its external appearance alone.

Multiple Simultaneous Views

In visualization systems where large data spaces are represented, it is common to have one window that shows an overview and several others that show expanded details. The major perceptual problem with the use of multiple windows is that detailed information in one window is disconnected from the overview (context information) shown in another. A solution is to use lines to connect the boundaries of the zoom window to the source image in the larger view. Figure 10.14 illustrates a zooming window interface for an experimental calendar application. Day, month, and year are shown as tables in separate windows, which are connected by triangular areas that integrate the focus information in one table within the context provided by another (Card et al., 1994).

The great advantage of the multiple window technique over the others listed previously is that it does not distort and it is able to show focus and context simultaneously. Its main disadvantage is the cost of setting up and manipulating extra windows.

If we have multiple views simultaneously, then the links between views can be made visually explicit (Ware & Lewis, 1995). Figure 10.15 shows an attached window used in a 3D zooming user interface. The method includes a viewpoint proxy, a transparent pyramid showing the direction and angle of the tethered view, and lines that visually link the secondary window with its source (Plumlee & Ware, 2003).

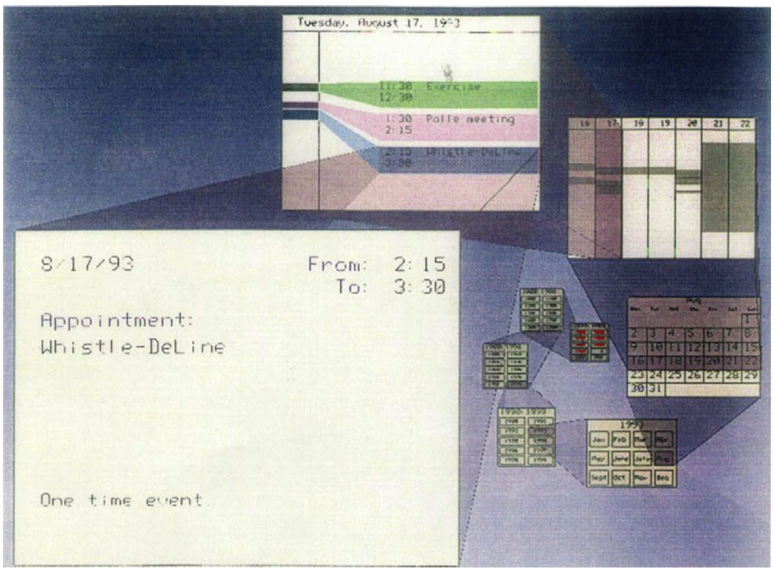


Figure 10.14 The spiral calendar (Mackinlay et al., 1994). The problem with multiple windows is that information can become visually fragmented. In this application, information in one window is linked to its context in another by a connecting transparent wedge.

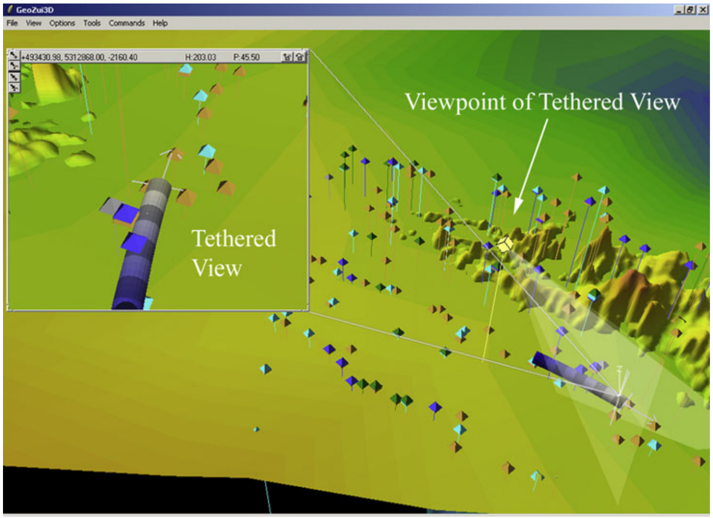


Figure 10.15 An attached window in GeoZui3D.

Evidence from usage suggests that the use of multiple windows with view proxies can be effective with scale differences of at least a factor of 30, meaning that this method is preferable to distortion methods where there is a larger difference between focus and context information.

> **[G10.15]** For large 2D or 3D data spaces, consider providing one or more windows that show a magnified part of the larger data space. These can support a scale difference of up to 30 times. In the overview, provide a visual proxy for the locations and directions of the magnified views.

Conclusion

We have been emphasizing the use of spatial maps to help in navigating data spaces; however, keep in mind that maps are not always the best answer. Consistent layout is essential for spatial memory to support revisiting an information entity having a spatial representation. Providing maps of the Internet, for example, has been tried many times, yet they have not proven useful. The Internet is vast and dynamic, and many representations of the same information are often required depending on what we are looking for. All of these factors mean that generating consistent maps is difficult if not impossible; any one map will necessarily provide only a partial view of some aspect of the available data. Procedural instructions can be more useful when the task itself requires navigating from data object to data object, taking certain actions at each. In this case, the cognitive representation of the task is likely to be topological and process oriented, not spatial.

Another caveat must be added to some of the guidelines that have been provided. We have been discussing navigating a data space as quickly and transparently as possible. Doing so involves supporting eye–hand coordination, using well-chosen interaction metaphors, and providing rapid and consistent feedback. The word *transparent* in user interface design is a metaphor for an interface that is so easy to use that it all but disappears from consciousness, but transparency can also come from practice, not just good initial design. A violin has an extraordinarily difficult user interface, and to reach virtuosity may take thousands of hours, but once virtuosity is achieved the instrument will have become a transparent medium of expression. This highlights a thorny problem in the development of novel interfaces. It is very easy for the designer to become focused on the problem of making an interface that can be used quickly by the novice, but it is much more difficult to research and develop designs for the expert. It is almost impossible to carry out experiments on expert use of radical new interfaces for the simple reason that no one will ever spend enough time on a research prototype to become truly skilled. Also, someone who has spent thousands of hours navigating using a set of buttons on a game controller will find that particular user interface easy to use and natural, even though novices find it very difficult. This means that even a poorly designed user interface may be best for a user population that is already highly skilled with it.

One of the goals of cognitive systems design is to tighten the loop between human and computer, making it easier for the human to obtain important information from the computer via the display. Simply shortening the amount of time it takes to acquire a piece of information may seem like a small thing, but human visual and verbal working memories are very limited in capacity and the information stored is easily lost; even a few seconds of delay or an increase in the cognitive load can drastically reduce the rate of information uptake by the user. When a user must stop thinking about the task at hand and switch attention to the computer interface itself, the effect can be devastating to the thought process. The result can be the loss of all or most of the cognitive context that has been set up to solve the real task. After such an interruption, the train of thought must be reconstructed. Research on the effect of interruptions tells us that this can greatly reduce cognitive productivity (Field & Spence, 1994; Cutrell et al., 2000).

CHAPTER ELEVEN

Visual Thinking Processes

Many visualization systems are designed to help us hunt for new information, so different designs can be evaluated in terms of the efficiency with which knowledge can be gained. Pirolli and Card (1995) drew the following analogy between the way animals seek food and the way people seek information. Animals minimize energy expenditure to get the required gain in sustenance; humans minimize effort to get the necessary gain in information. Foraging for food has much in common with seeking information because, like edible plants in the wild, morsels of information are often grouped but separated by long distances in an information wasteland. Pirolli and Card elaborated the idea to include information "scent"—like the scent of food, this is the information in the current environment that will assist us in finding more succulent information clusters.

Reducing the cost of knowledge requires that we optimize cognitive algorithms that run on a peculiar kind of hybrid computer; part of this computer is a human brain, including its visual system, and part is a digital computer with a graphical display. In Chapter 1 we discussed user costs and benefits, but now we take a more system-oriented view with the following overarching principle for this chapter:

[G11.1] Design cognitive systems to maximize cognitive productivity.

Cognitive productivity is the amount of valuable cognitive work done per unit of time. Although it is only possible to put a value on this some of the time, maximizing productivity is nevertheless the (often implicit) goal of systems designed to support

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knowledge workers. In this chapter, we will be examining the characteristics of human–computer cognitive systems and the algorithms that run on them in order to better design systems that increase cognitive throughput.

The Cognitive System

An interactive visualization can be considered an internal interface between human and computer components in a problem-solving system. We are all becoming cognitive cyborgs in the sense that a person with a computer-aided design program, access to the Internet, and other software tools is capable of problem-solving strategies that would be impossible for that person acting unaided. A business consultant plotting projections based on a spreadsheet business model can combine business knowledge with the computational power of the spreadsheet to plot scenarios rapidly, interpret trends visually, and make better decisions.

Figure 11.1 illustrates the key components of this kind of cognitive system. On the human side, a critical component is visual working memory; we will be concerned especially with the constraints imposed by its low capacity. At any given instant, visual working memory contains a small amount of information relating to the visual display generated by a computer. It can also contain information about the *visual query* that is being executed by means of a visual pattern search.

For visual queries to be useful, a problem must first be cast in the form of a visual pattern that, if identified, helps solve part of the problem. Finding a number of big red circles in a geographic information system (GIS) display, for example, may indicate a problem with water pollution. Finding a long, red, fairly straight line on a map can show the best way to drive between two cities. Once the visual query is constructed, a visual pattern search provides answers.

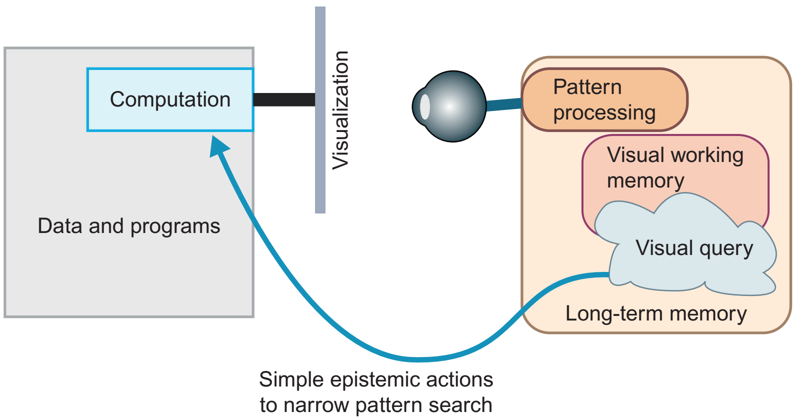


Figure 11.1 The cognitive system considered in this chapter.

Part of the thinking process consists of what Karsh (2009) calls *epistemic actions*. These can be eye movements to pick up more information. Or, in the case of an interactive visualization, these can be mouse movements, causing programs to execute in the computer, changing the nature of the information that is displayed. These computer-side operations, such as brushing to highlight related information or zooming in on some information, make it easier to process visual queries by finding task-relevant patterns. Alternatively, the selection of a visual object may trigger the highlighting of other objects that a computer algorithm suggests are relevant. This narrows the visual search, speeding the resolution of a visual query. We will focus here mostly on tight loop interactions, where human actions trigger relatively simple and rapid transformations of what is presented on a display.

Another important role of visualizations is as a form of memory extension. This comes about from the way a displayed symbol, image, or pattern can rapidly evoke nonvisual information and cause it to be loaded from long-term memory into verbal/propositional processing centers.

The most important contribution of this chapter is a set of *visual thinking algorithms*. These are processes executed partly in the brain of a person and partly in a computer, but there is an essential component of visual perception that we need to describe first. We have so far neglected visual memory and its relationship to nonvisual memory as well as attention, and how these processes are critical to understanding visual thinking; therefore, the first third of this chapter is devoted to memory systems, following which the algorithms are described.

Memory and Attention

As a first approximation, there are three types of memory: iconic, working, and long-term (see Figure 11.2). There may also be a fourth, intermediate store that determines which information from working memory finds its way into long-term memory.

Iconic memory is a very short-term image store, holding what is on the retina until it is replaced by something else or until several hundred milliseconds have passed (Sperling, 1960). This is image-related information, lacking semantic content.

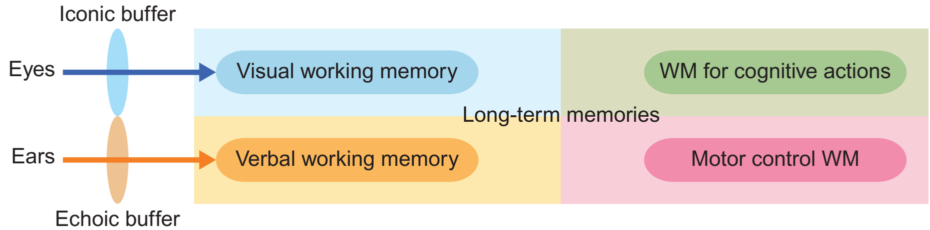


Figure 11.2 Three types of memories are iconic stores, working memory stores, and long-term memory stores.

Visual working memory holds the visual objects of immediate attention. The contents of working memory can be drawn from either long-term memory (in the case of mental images) or input from the eye, but most of the time information in working memory is a combination of external visual information made meaningful through the experiences stored in long-term memory.

Long-term memory is the information that we retain from everyday experience, perhaps for a lifetime, but it should not be considered as separate from working memory. Instead, working memory can be better conceived of as information activated within long-term memory.

Of the three different stores, working memory capacities and limitations are most critical to the visual thinking process.

Working Memories

There are separate working memory subsystems for processing auditory and visual information, as well as subsystems for body movements and verbal output (Thomas et al., 1999). There may be additional working memory stores for sequences of cognitive instructions and for motor control of the body. Kieras and Meyer (1997), for example, proposed an amodal control memory containing the operations required to accomplish current goals and a general-purpose working memory containing other miscellaneous information. A similar control structure is called the *central executive* in Baddeley and Hitch's (1974) model. A more modern view is that there is no central processor; instead, different potential activation loops compete with a winner-take-all mechanism, causing only one to become active. This determines what we will do next (Carter et al., 2011).

Visual thinking is only partly executed using the uniquely visual centers of the brain. In fact, it emerges from the interplay of visual and nonvisual systems, but because our subject is visual thinking we will hereafter refer to most nonvisual processes generically as *verbal–propositional processing* (see Chapter 9 for a discussion of the issues relating to representations based on words and images). It is functionally quite easy to separate visual and verbal–propositional processing. Verbal–propositional subsystems are occupied when we speak, whereas visual subsystems are not. This allows for simple experiments to separate the two processes. Postma and De Haan (1996) provided a good example. They asked subjects to remember the locations of a set of easily recognizable objects—small pictures of cats, horses, cups, chairs, tables, etc.—laid out in two dimensions on a screen. The objects were then placed in a line at the top of the display and the subjects were asked to reposition them in their original locations, a task the subjects performed quite well. In another condition, subjects were asked to repeat a nonsense syllable, such as "blah," while in the learning phase. This time, they did much worse. Saying "blah" did not disrupt memory for the locations themselves; instead, it only disrupted memory for what was at the locations. This was demonstrated by having subjects place a set of disks at the positions of the original objects, which they could do with relative accuracy. In other words, when "blah" was said in the learning phase, subjects learned a set of locations but not the objects at those locations. This technique is called *articulatory suppression*. The reason why saying "blah" disrupted working memory for the objects is that task-relevant object information was stored using a verbal–propositional coding. The reason it did not disrupt location information is because place information was held in visual working memory.

Visual Working Memory Capacity

Visual working memory can be roughly defined as the visual information retained from one fixation to the next. Position is not the only information stored in visual working memory; some abstract shape, color, and texture information is also retained. This appears to be limited to about three to five simple objects (Irwin, 1992; Luck & Vogel, 1997; Melcher, 2001; Xu, 2002). The exact number depends on the task and the kind of pattern.

Figure 11.3(a) illustrates the kinds of patterns used in a series of experiments by Vogel et al. (2001) to study the capacity of visual working memory. In these experiments, one set of objects was shown for a fraction of a second (e.g., 0.4 sec), followed by a blank of more than 0.5 sec. After the blank, the same pattern was shown, but with one attribute of an object altered—for example, its color or shape. The results from this and a large number of similar studies have shown that about three objects can be retained without error, but these objects can have color, shape, and texture. If the same amount of color, shape, and texture information is distributed across more objects, memory declines for each of the attributes.

Only quite simple shapes can be stored in this way. Each of the mushroom shapes shown in Figure 11.3(b) uses up two visual memory slots (Xu, 2002). Subjects do no better if the stem and the cap are combined than if they are separated. Intriguingly, Vogel et al. (2001) found that if colors were combined with concentric squares, as shown in Figure 11.3(c), then six colors could be held in visual working memory, but if they were put in side-by-side squares, then only three colors could be retained.

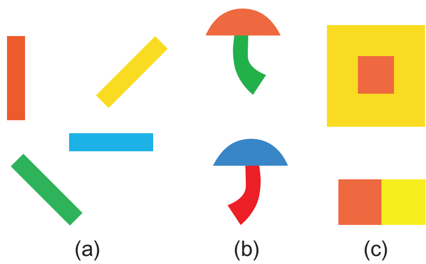


Figure 11.3 Patterns used in studies of the capacity of visual working memory. (*(a, c) From Vogel et al. (2001). (b) From Xu (2002). Reproduced with permission.*)

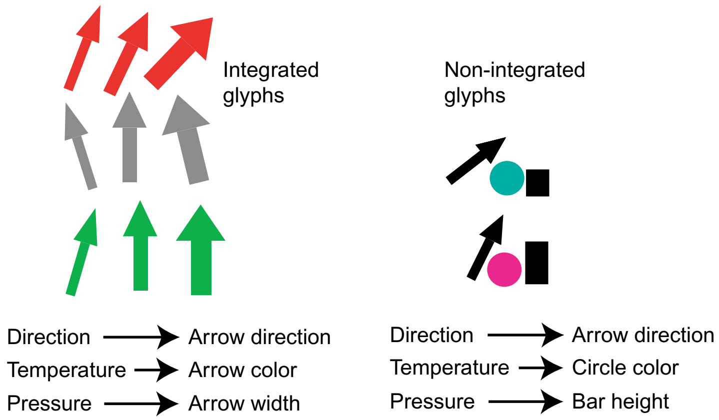


Figure 11.4 If multiple data attributes are integrated into a single glyph, more information can be held in visual working memory.

Melcher (2001) found that more information could be retained if longer viewing was permitted, up to five objects after a 4-sec presentation.

What are the implications for data glyph design? (A glyph, as discussed in Chapter 5, is a visual object that displays one or more data variables.) If it is important that a data glyph be held in visual working memory, then it is important that its shape allows it to be encoded according to visual working memory capacity. Figure 11.4 shows two ways of representing the same data. One consists of an integrated glyph containing a colored arrow showing orientation by arrow direction, temperature by arrow color, and pressure by arrow width. A second representation distributes the three quantities among three separate visual objects: orientation by an arrow, temperature by the color of a circle, and air pressure by the height of a rectangle. The theory of visual working memory and the results of Vogel et al. (2001) suggest that three of the integrated glyphs could be held in visual working memory, but only one of the nonintegrated glyphs.

Change Blindness

The finding that visual working memory has a very low capacity has extraordinary implications for how we see and what we see in general, as well as how we interpret visualizations. Among other things it suggests that our impression that we see the world in all its complexity and detail is illusory. In this section, we review some of the evidence showing that this is in fact the case.

One of the consequences of the very small amount of information held in visual working memory is a phenomenon known as *change blindness* (Rensink, 2000). Because we remember so little, it is possible to make large changes in a display between one view and the next, and people generally will not notice unless the change is to something they have recently attended. If a change is made while the display is being fixated, the rapid visual transition will draw attention to it. But, if changes are made mid-eye movement, mid-blink, or after a short blanking of the screen (Rensink, 2002), then the change generally will not be seen. Iconic memory information in retinal coordinates decays within about 200 msec (Phillips, 1974). By the time 400 msec have elapsed, what little remains is in visual working memory.

An extraordinary example of change blindness is a failure to detect a change from one person to another in mid-conversation. Simons and Levin (1998) carried out a study in which an unsuspecting person was approached by a stranger holding a map and asking for directions. The conversation that ensued was interrupted by two workers carrying a door and during this interval another actor, wearing different clothes, was substituted to carry on the conversation. Remarkably, most people did not notice the substitution.

To many people, the extreme limitation on the capacity of visual working memory seems quite incredible. How can we experience a rich and detailed world, given such a shallow internal representation? Part of the answer to this dilemma is that the world "is its own memory" (O'Regan, 1992). We perceive the world to be rich and detailed, not because we have an internal detailed model, but simply because whenever we wish to see detail we can get it, either by focusing attention on some aspect of the visual image at the current fixation or by moving our eyes to see the detail in some other part of the visual field. We are unaware of the jerky eye movements by which we explore the world and only aware of the complexity of the environment through detail being brought into working memory on a need-to-know, just-in-time fashion (O'Regan, 1992; Rensink et al., 1997; Rensink, 2002).

A second part of the explanation of how we sustain the illusion of seeing a rich and detailed word is *gist*. Gist is the activated general knowledge we have about particular kinds of environments. Much of the information we think we are perceiving externally is not external at all, but is contained in the gist already stored in our long-term memories. So, in an instant what we actually perceive consists of a little bit of external information and a lot of internal information from long-term memory. We are seeing, mostly, what we already know about the world. To this is added the implicit, unconscious knowledge that we can rapidly query the external world for more information by means of a rapid eye movement. No sooner do we think of some information that we need than we have it at the point of fixation. This gives rise to the illusion that we see the whole world in detail.

Spatial Information

For objects acquired in one fixation to be reidentified in the next fixation requires some kind of buffer that holds locations in egocentric coordinates as opposed to retina-centric coordinates (Hochberg, 1968). This also allows for a very limited synthesis of information obtained from successive fixations.

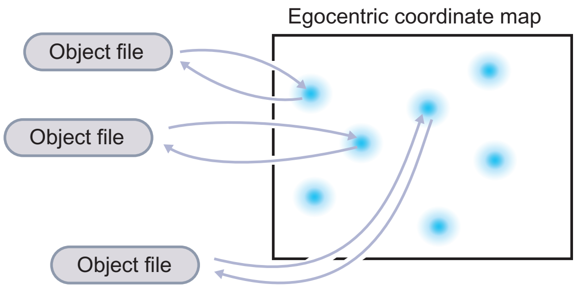


Figure 11.5 A spatial map of a small number of objects recently held by attention in working memory.

Neurophysiological evidence from animal studies suggests that the lateral interparietal area near the top of the brain (Colby, 1998) appears to play a crucial role in linking retinocentric coordinate maps in the brain with egocentric coordinate maps. Egocentric–spatial location memory also holds remarkably little information, although probably a bit more than the three objects that Vogel et al. (2001) suggested. It may be possible to remember some information about approximately nine locations (Postma et al., 1998). Three of these may contain links to object files (introduced in Chapter 8), whereas the remaining ones specify only that there is something at a particular region in space, but very little more. Figure 11.5 illustrates the concept.

A recent and very intriguing study by Melcher (2001) suggests that we can build up information about a few scenes that are interspersed. When the background of a scene was shown, subjects could recall some of the original objects, even though several other scenes had intervened. This implies that a distinctive screen design could help with visual working memory when we switch between different views of a data space. We may be able to cognitively swap in and swap out some retained information for more than one data "scene," albeit each with a very low level of detail.

An interesting question is how many moving targets can be held from one fixation to the next. The answer seems to be about four or five. Pylyshyn and Storm (1988) carried out experiments in which visual objects moved around on a display in a pseudo-random fashion. A subset of the objects was visually marked by changing color, but then the marking was turned off. If there were five or fewer marked objects, subjects could continue to keep track of them, even though they were now all black. Pylyshyn coined the term *FINST*, for fingers of instantiation, to describe the set of pointers in a cognitive spatial map that would be necessary to support this task. The number of individual objects that can be tracked is somewhat larger than the three found by Vogel et al. (2001), although it is possible that the moving objects may be grouped perceptually into fewer chunks (Yantis, 1992).

Attention

Experiments showing that we can hold three or four objects in visual working memory required intense concentration on the part of the participants. Most of the time, when we interact with displays or just go about our business in the everyday world, we will not be attending that closely. In a remarkable series of studies, Mack and Rock (1998) tricked subjects into not paying attention to the subject of the experiment, although they wanted to make sure that subjects were at least looking in the right direction. They told subjects to attend to an X-shaped pattern for changes in the length of one of the arms; perfect scores on this task indicated they had to be attending. Then the researchers presented a pattern that the subject had not been asked to look for. They found that even though the unexpected pattern was close to, or even on, the point of fixation, most of the time it was not seen. The problem with this kind of study is that the ruse can only be used once. As soon as you ask subjects if they saw the unexpected pattern, they will start looking for unexpected patterns. Mack and Rock therefore used each subject for only one trial; they used hundreds of subjects in a series of studies.

Mack and Rock called the phenomenon *inattentional blindness*. It should not be considered as a peculiar effect only found in the laboratory. Instead, this kind of result probably reflects everyday reality much more accurately than the typical psychological experiment in which subjects are paid to closely attend. Most of the time we simply do not register what is going on in our environment unless we are looking for it. The conclusion must be that attention is central to all perception.

Although we are blind to many changes in our environment, some visual events are more likely to cause us to change attention than others are. Mack and Rock found that although subjects were blind to small patterns that appeared and disappeared, they still noticed larger visual events, such as patterns larger than one degree of visual angle appearing near the point of fixation.

Visual attention is not strictly tied to eye movements. Although attending to some particular part of a display often does involve an eye movement, there are also attention processes operating within each fixation. The studies of Treisman and Gormican (1988) and others (discussed in Chapter 5) showed that we process simple visual objects serially at a rate of about one every 40 to 50 msec. Because each fixation typically will last for 100 to 300 msec, this means that our visual systems process between two and six simple objects or shapes within each fixation before we move our eyes to attend visually to some other region.

Attention is also not limited to specific locations of a screen. We can, for example, choose to attend to a particular pattern that is a component of another pattern, even though the patterns overlap spatially (Rock & Gutman, 1981). These query-driven tuning mechanisms were discussed in Chapter 6. As discussed, the possibility of choosing to attend to a particular attribute depends on whether or not it is preattentively

RED GREEN YELLOW BLUE BLACK GREEN PURPLE BLUE BLACK
ORANGE GREEN RED GREEN YELLOW BLUE BLACK GREEN
PURPLE BLUE BLACK ORANGE BLACK GREEN RED

GREEN RED BLUE YELLOW PURPLE RED BLACK BLUE BLACK
GREEN ORANGE BLUE RED PURPLE YELLOW RED BLACK
YELLOW GREEN ORANGE BLACK GREEN RED GREEN

Figure 11.6 As quickly as you can, try to name the colors in the set of words at the top, and then try to name the colors in the set of words below. Even though they are asked to ignore the meaning of the words, people are slowed down by the mismatch in the second set. This is referred to as the *Stroop effect*, which shows that some processing is automatic.

distinct (Treisman, 1985); for example, if a page of black text has some sections highlighted in red, we can choose to attend only to the red sections, easily ignoring the rest. Having whole groups of objects that move is especially useful in helping us to attend selectively (Bartram & Ware, 2002). We can attend to the moving group or the static group, with relatively little interference between them.

The selectivity of attention is by no means perfect. Even though we may wish to focus on one aspect of a display, other information is also processed, apparently to quite a high level. The well-known *Stroop effect* illustrates this (Stroop, 1935). In a set of words printed in different colors, as illustrated in Figure 11.6, if the words themselves are color names that do not match the ink colors, subjects name the ink colors more slowly than if the colors match the words. This means that the words are processed automatically; we cannot entirely ignore them even when we want to. More generally, it is an indication that all highly learned symbols will automatically invoke verbal–propositional information that has become associated with them. But, still, these crossover effects are relatively minor. The main point is that the focus of attention largely determines what we will see, and this focus is set by the task we are undertaking.

Jonides (1981) studied ways of moving a subject's attention from one part of a display to another. He looked at two different ways, which are sometimes called *pull cues* and *push cues*. In a pull cue, a new object appearing in the scene pulls attention toward it. In a push cue, a symbol in the display, such as an arrow, tells someone where a new pattern is to appear. Pull cues are faster; it takes only about 100 msec to shift attention based on a pull cue but can take between 200 and 400 msec to shift attention based on a push cue.

Object Files, Coherence Fields, and Gist

In Chapter 8, we introduced the term *object file* from Kahneman et al. (1992) to describe the grouping of visual and verbal attributes into a single entity held in working memory. Now we shall consider the needs of cognition in action and argue that considerably richer bundles of information come into being and are held briefly, tying together both perception and action.

Providing context for an object that is perceived is the gist of a scene. Gist is used mainly to refer to the properties that are pulled from long-term memory as the image is recognized. Visual images can activate this verbal–propositional information in as little as 100 msec (Potter, 1976). Gist consists of both visual information about the typical structure of an object and links to relevant nonvisual information. The gist of a scene contains a wealth of general information that can help guide our actions, so that when we see a familiar scene (for example, the interior of a car) a visual framework of the typical locations of things will be activated.

Rensink (2002) developed a model that ties together many of the components we have been discussing. This is illustrated in Figure 11.7. At the lowest level are the elementary visual features that are processed in parallel and automatically. These correspond to elements of color, edges, motion, and stereoscopic depth. From these elements, prior to focused attention, low-level precursors of objects, called proto-objects, exist in a continual state of flux. At the top level, the mechanism of attention forms different visual objects from the proto-object flux. Note that Rensink's proto-objects are located at the top of his "low-level vision system." He is not very specific on the nature of proto-objects, but it seems reasonable to suppose that they have characteristics similar to the mid-level pattern perception processes in the three-stage model laid out in this book.

Rensink uses the metaphor of a hand to represent attention, with the fingers reaching down into the proto-object field to instantiate a short-lived object. After the grasp of attention is released, the object loses its coherence, and the components fall back into the constituent proto-objects. There is little or no residue from this attentional process.

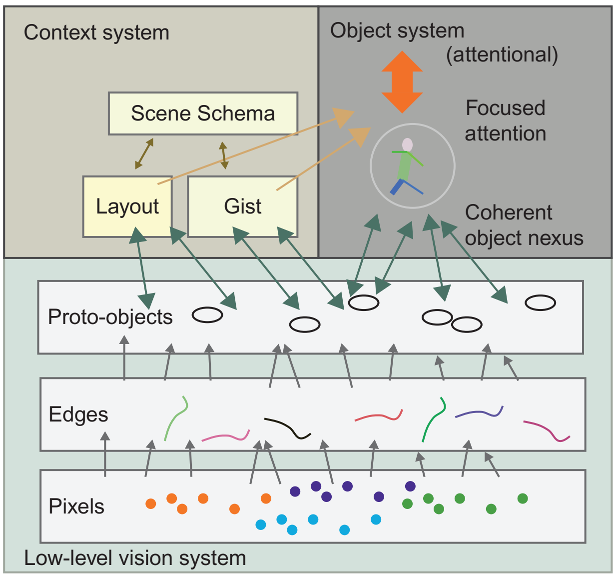


Figure 11.7 A summary of the components of Rensink's (2002) model of visual attention.

Other components of the model are a layout map containing location information and the rapid activation of object gist. The central role of attention in Rensink's model suggests a way that visual queries can be used to modify the grasp of attention and pull out the particular patterns we need to support problem solving. We might need to know, for example, how one module connects to another in a software system. To obtain this information, a visual query is constructed to find out if lines connect certain boxes in the diagram. This query is executed by focusing visual attention on those graphical features.

There is also recent evidence that task-specific information needed to support actions relating to visual objects is bound together with the objects themselves (Wheeler & Treisman, 2002). This broadens the concept of the object file still further.

The notion of proto-objects in a continuous state of flux also suggests how visual displays can provide a basis for creative thinking, because they allow multiple visual interpretations to be drawn from the same visualization. Another way to think about this is that different patterns in the display become cognitively highlighted, as we consider different aspects of a problem.

Long-Term Memory

Long-term memory contains the information that we build up over a lifetime. We tend to associate long-term memory with events we can consciously recall—this is called *episodic memory* (Tulving, 1983). Most long-term memory research has used verbal materials, but long-term memory also includes motor skills, such as the finger movements involved in typing, as well as the perceptual skills, integral to our visual systems, that enable us to rapidly identify words and thousands of visual objects. What we can consciously recall is only the tip of the iceberg.

There is a common myth that we remember everything we experience but we lose the indexing information; in fact, we remember only what gets encoded in the first 24 hours or so after an event occurs. The best estimates suggest that we do not actually store very much information in long-term memory. Using a reasonable set of assumptions, Landauer (1986) estimated that only a few hundred megabytes of information are stored over a lifetime. It is much less than what can currently be found in the solid-state main memory of a smart phone. Another way of thinking about it is that on average we are acquiring about 2 bits of new information per waking second. The power of human long-term memory, though, is not in its capacity but in its remarkable flexibility. The reason why human memory capacity can be so small is that most new concepts are made from existing knowledge, with minor additions, so there is little redundancy. The same information is combined in many different ways and through many different kinds of cognitive operations.

Human long-term memory can be usefully characterized as a network of linked concepts (Collins & Loftus, 1975; Yufic & Sheridan, 1996). Once a concept is activated and brought to the level of working memory, other related concepts become partially activated; they are ready to go. Our intuition supports this model. If we think of a particular concept—for example, data visualization—we can easily bring to mind a set of related concepts: computer graphics, perception, data analysis, potential applications. Each of these concepts is linked to many others.

The network model makes it clear why some ideas are more difficult to recall than others. Concepts and ideas that are distantly related naturally take longer to find; it can be difficult to trace a path to them and easy to take wrong turns in traversing the concept net, because no map exists. For this reason, it can take minutes, hours, or even days to retrieve some ideas. A study by Williams and Hollan (1981) investigated how people recalled names of classmates from their high-school graduating class, 7 years later. They continued to recall names for at least 10 hours, although the number of falsely remembered names also increased over time. The forgetting of information from long-term memory is thought to be more of a loss of access than an erasure of the memory trace (Tulving & Madigan, 1970). Memory connections can easily become corrupted or misdirected; as a result, people often misremember events with a strong feeling of subjective certainty (Loftus & Hoffman, 1989).

Long-term memory, like working memory, appears to be distributed and specialized into subsystems. Long-term visual memory involves parts of the visual cortex, and long-term verbal memory involves parts of the temporal cortex specialized for speech. More abstract and linking concepts may be represented in areas such as the prefrontal cortex.

What about purely visual long-term memory? It does not appear to contain the same kind of network of abstract concepts that characterizes verbal long-term memory; however, there may be some rather specialized structures in visual scene memory. Evidence for this comes from studies showing that we identify objects more rapidly in the right context, such as bread in a kitchen (Palmer, 1975). The power of images is that they rapidly evoke verbal–propositional memory traces; we see a cat and a whole host of concepts associated with cats becomes activated. Images provide rapid evocation of the semantic network, rather than forming their own network (Intraub & Hoffman, 1992). To identify all of the objects in our visual environment requires a great store of visual appearance information. Biederman (1987) estimated that we may have about 30,000 categories of visual information.

Consolidation of information into long-term memory only occurs when active processing is done to integrate the new information with existing knowledge (Craik & Lockhart, 1972). Although there are different kinds of long-term memory stored in different areas of the brain, there is a specialized structure in the midbrain called the *hippocampus* (Small et al., 2001) that is critical to all memory consolidation. If people have damage in this area they lose the ability to form new long-term memories, although they retain ones they had from before the damage.

The dominant theory about how long-term memories are physically stored is that they are traces—neural pathways made up of strengthened connections between the hippocampus and areas of the cortex specialized for different kinds of information. Recall consists of the activation of a particular pathway (Dudai, 2004). So, working memory consists of activated circuits that are embodiments of long-term memories. This explains the phenomenon that *recognition* is far superior to *recall*. As visual information is processed through the visual system, it activates the long-term memory traces of visual objects that have previously been processed by the same system. In recognition, a visual memory trace is being reawakened. In recall, it is necessary for us to actually describe some pattern, by drawing it or using words, but we may not have access to the memory trace. In any case, the memory trace will not generally contain sufficient information for reconstructing an object. Recognition only requires enough information that an object can be differentiated from other objects.

The memory trace theory also explains *priming* effects; if a particular neural circuit has recently been activated, it becomes easier to activate again, hence it is primed for reactivation. It is much easier to recall something that we have recently had in working memory. Seeing an image will prime subsequent recognition so we identify it more rapidly the next time (Bichot & Schall, 1999).

Chunks and Concepts

Human memory is much more than a simple repository like a telephone book; information is highly structured in overlapping and interconnected ways. The term *chunk* and the term *concept* are both used in cognitive psychology to denote important units of stored information. The two terms are used interchangeably here. The process of grouping simple concepts into more complex ones is called *chunking*. A chunk can be almost anything: a mental representation of an object, a plan, a group of objects, or a method for achieving some goal. The process of becoming an expert in a particular domain is largely one of creating effective high-level concepts or chunks. Chunks of information are continuously being prioritized, and to some extent reorganized, based on the current cognitive requirements (Anderson & Milson, 1989).

Knowledge Formation and Creative Thinking

One theory of the way concepts are formed and consolidated into long-term memories is through repeated associations between events in the world, establishing or strengthening neural pathways. This is called the *Bayesian* approach after the famous originator of this essentially statistical theory. The majority of learning, however, occurs on a single exposure, ruling out a statistical theory that relies on many repeated co-occurrences to build connections.

As an alternative to the Bayesian theory is the idea that new concepts are built on existing concepts, and ultimately all are derived from models gleaned from our early interactions with the physical world. This theory allows for single event learning of new concepts, something that should not happen according to Bayesian theory, but which is commonly observed in studies of infants.

According to this view, concepts are tied to the sensory modality of the formative experiences. In particular, causal concepts are generally based on a kind of approximate modeling based on everyday physics. Wolff (2007) calls this the *physicalist* theory. Leslie (1984) suggested that concepts relating to physical causation are processed by a primitive "theory of bodies" that schematizes objects as bearers, transmitters, and recipients of primitive encodings of forces.

A basic assumption of physicalist theories is that physical causation is cognitively more basic than nonphysical causation, such as social or psychological causal factors. Supporting this is evidence that our ability to perceive physical causation first develops in infants at around 3 to 4 months, earlier than the ability to perceive social causation, which occurs around 6 to 8 months (Cohen et al., 1998). In addition, Wolff (2007) showed that a dynamics model is accepted as a representation of social causation.

The theory that cognitive concepts are based on sensory experiences has a long history, being set out by John Locke in the 15th century and even earlier by Aristotle. This theory fell out of favor in the 1980s and 1990s but has relatively recently undergone a major renaissance. Barsalou (1999) argued that sensory experiences of time-varying events are stored as neural activation sequences, and that these sequences act both as memories and as executable processes that can be used in future activities. It is proposed that these processes become the substrate of reasoning about events in the world (Glenberg, 1997). Also, linguists such as Pinker (2007) and Lakoff and Johnson (1980) point to the enormous richness of spatial and temporal metaphors in thought, as revealed by language, showing that highly abstract concepts are often based on concepts that have a basis in the spatial and temporal physics of everyday life.

Knowledge Transfer

Once we take the position that novel concepts are based on a scaffolding of existing concepts, the critical question becomes how and under what circumstances does this occur? It is generally thought that new concepts are formed by a kind of hypothesis-testing process (Levine, 1975). According to this view, multiple tentative hypotheses about the structure of the world are constantly being evaluated based on sensory evidence and evidence from internal long-term memory. In most cases, the initial hypotheses start with some existing concept, a mental model or metaphor. New concepts are distinguished from the prototype by means of transformations (Posner & Keele, 1968).

A study by Goldstone and Sakamoto (2003) applied the physicalist theory to show how even a very abstract concept can be generalized. They studied the problem of teaching a powerful class of computer algorithms called *simulated annealing*. These borrow a metaphor from the field of metallurgy and make use of controlled randomness to solve problems. These methods are also based on another methophoric idea called *hill climbing*, which we need to understand first. In hill climbing a problem space is imagined metaphorically as a terrain with hills and valleys. The best solution is the top of the highest peak. Goldstone actually inverted the metaphor and considered the best solution to be the bottom of deepest hollow, the lowest point on the terrain. The hill climbing method involves starting at some random point in the problem space and moving upward. The valley descending counterpart involves finding a random point and moving downward—think of a marble rolling down a hill. In either case, a problem with this algorithm is that the marble can get stuck in a small local valley, not the best solution.

To help students understand how simulated annealing can help with hill climbing, Goldstone and Sakamoto gave students the interfaces shown in Figure 11.8. Red dots rained downward and when they hit the green hills they slid down into the valleys. The result, as shown, is that most of the dots find the best solution at the bottom of the deepest valley, but some get stuck in a smaller valley that is less than optimal. Students could improve the success rate with a slider that caused a controlled amount of randomness to be injected. In this case, the red dots bounced when they hit the terrain, in a random direction, with the amount of scattering being determined by the slider. Students were able to learn through this interactive interface how the best solutions came about by starting with a lot of randomness (the dots bounced a lot) and then decreasing it over time. This is how simulated annealing works.

But, could they transfer the knowledge they had gained? In order to measure knowledge transfer, they had students try to solve a very different problem, finding the best path between two points in a space filled with obstacles. This second problem is illustrated in Figure 11.9. In this example, the students were told that the random points are connected into an underlying (not visible) linked list and spring forces pull adjacent points together. Simply pulling the points would not result in a solution because they could get stuck on the obstacles that fill the space. The addition of randomness, through simulated annealing, can solve this problem, too.

One of the student participants said:

> *Sometimes the balls get stuck in a bad configuration. The only way to get them unstuck is to add randomness to their movements. The randomness jostles them out of their bad solution and gives them a chance to find a real path.*

Goldstone and Sakamoto showed that students were able to transfer knowledge from one problem to another thereby gaining a deeper understanding. They also found other interesting things. For the students with weaker understanding, greater transfer was obtained if there were more superficial differences between the two simulations (to achieve this, color similarities were removed). Also, another experiment showed that a certain degree of abstraction helped. If soccer balls were used instead of abstract points, knowledge transfer was reduced.

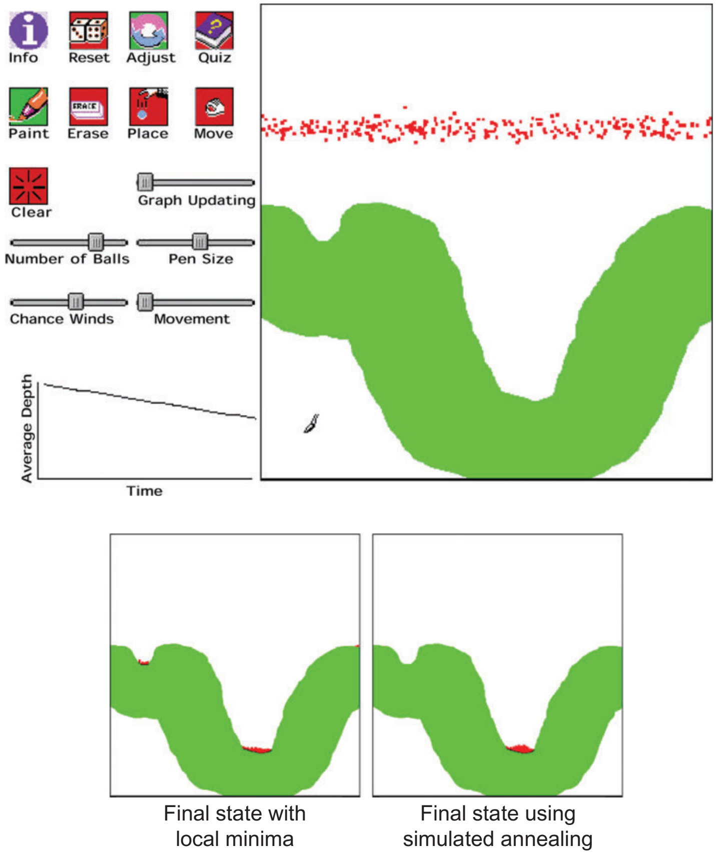


Figure 11.8 Screens from a user interface designed to teach students the concept of simulated annealing. (*From Goldstone & Sakamoto (2003). Reproduced with permission.*)

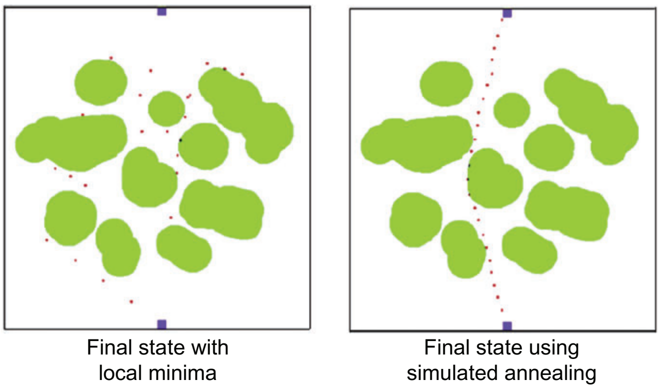


Figure 11.9 Finding a path through a set of obstacles can also be done through simulated annealing (*From Goldstone & Sakamoto (2003). Reproduced with permission.*)

The results of this study support the theory that showing two different problems with the same underlying solution can produce a deeper understanding. They also warn against making animations too concrete. There is a tendency in educational software to dress up animations with appealing characters and attractive drawings. Goldstone and Sakamoto's work suggests that this may be a serious mistake.

Visualizations and Mental Images

We now have one last piece of mental capacity to explore. People can, to some extent, build diagrams in their heads without the aid of external inputs. These mental images are important because the mental operations involved in reasoning with visualizations very often involve combinations of mental imagery and external imagery.

The following are key properties of mental images:

- Mental images are transitory, maintained only by cognitive effort and rapidly fading without it (Kosslyn, 1990).
- Only relatively simple images can be held in mind, at least for most people. Kosslyn (1990) had subjects add more and more imaginary bricks to a mental image. What they found was that people were able to imagine four to eight bricks and no more. Because the bricks were all identical, however, it is almost certain that the limit he found would have been smaller for more complex objects—for example, a red triangle, a green square, a blue circle.
- People are able to form mental images of aggregations, such as a pile of bricks. This partially gets around the problem of the small number of items that can be imagined.
- Operations can be performed on mental images. Individual parts can be translated, scaled or rotated, and added, deleted, or otherwise altered (Shepard & Cooper, 1982).
- People sometimes use visual imagery when asked to perform logical problems (Johnson-Laird, 1983). For example, a person given the statement, "Some swans are black," might construct a mental image containing an aggregation of white dots (as a chunk) with a mental image of one or two black dots.
- Visual imagery uses the same neural machinery as normal seeing, at least to some extent. Studies using functional magnetic resonance imaging (fMRI) of the brain and conducted while subjects carried out various mental imaging operations have shown that parts of the visual system are activated. This includes activations of the primary visual cortex (Kosslyn & Thompson, 2003). Because no one doubts that mental imagery originates at higher level visual centers, this suggests top-down activation, with the lower levels providing a kind of canvas on which mental images are formed.

- Mental imagery can be combined with external imagery as part of the visual thinking process. This capability includes mental additions and deletions of parts of a diagram (Massironi, 2004; Shimojima & Katagiri, 2008). It also includes the mental labeling of diagram parts. Indeed, the mental attribution of meaning to parts of diagrams is fundamental to the perception of diagrams; this is how a network of dots and lines can be understood as communications links between computers. Cognitive relabeling can also occur, however. When thinking about the robustness of a network, for example, a communications engineer might imagine a state where a particular link in a diagram becomes broken.

Review of Visual Cognitive System Components

This section briefly summarizes the components of the cognitive machine that are needed in the construction of visual thinking algorithms.

Early Visual Processing

In early stage visual processing, the visual image is broken down into different kinds of features, particularly color differences, local edge and texture information, and local motion information. These form semi-independent channels, so that motion information, color information, and texture information are processed separately. The elements of shape share a channel with texture. In addition, the channel properties can predict what can be seen rapidly, and this tells us how best to highlight information. Each channel allows two to four distinct categories of information to be rapidly perceived.

Pattern Perception

Patterns are formed based on low-level features and on the task demands of visual thinking. Patterns consist of entities such as continuous contours, areas of a common texture, color, or motion. Only a few simple patterns can be held in working memory at any given instant.

Eye Movements

Eye movements are planned using the task-weighted spatial map of proto-patterns. Those patterns most likely to be relevant to the current task are scheduled for attention, beginning with the one weighted most significant. As part of this process, partial solutions are marked in visual working memory by setting placeholders in the egocentric spatial map.

The Intrasaccadic Scanning Loop

When our eyes alight on a region of potential interest, the information located there is processed serially. If we are looking for a simple visual shape among a set of similar shapes, the rate of processing is about 40 msec per item.

Working Memory

Based on incoming patterns and long-term knowledge, a small number of transitory nexii (or object files) are formed in working memory. Theorists disagree on details of exactly how visual working memory operates, but there is broad agreement on basic functionality and capacity—enough to provide a solid foundation for an understanding of the visual thinking process. Here is a list of some key properties of visual working memory:

- Visual working memory is separate from verbal working memory. Capacity is limited to a small number of simple visual objects and patterns, perhaps three to five simple objects.
- Part of working memory is a rough visual spatial map in egocentric coordinates that contains residual information about a small number of recently attended objects.
- Attention controls what visual information is held and stored.
- The time to change attention is about 100 msec.
- The semantic meaning or gist of an object or scene can be activated in about 100 msec. Gist also primes task-appropriate eye movement strategies.
- For items to be processed into long-term memory, deeper semantic coding is needed.
- To complete the processing into long-term memory, sleep is needed.
- A visual query pattern can be held in working memory, forming the basis for active visual search through the direction of attention.

Mental Imagery

Mental imagery is the ability to build simple images in the mind. More importantly for present purposes, mental images can be combined with external imagery as part of the construction and testing of hypotheses about data represented in a visualization.

Epistemic Actions

Epistemic actions are actions intended to help in the discovery of information, such as mouse selections or zooming in on a target. The lowest cost epistemic action is eye movement. Eye movements allow us to acquire a new set of informative visual objects in 100 to 200 msec. Moreover, information acquired in this way will be integrated readily with other information that we have recently acquired from the same space. Thus, the ideal visualization is one in which all the information for visualization is available on a single high-resolution screen. The cost of navigating is only a single eye movement or, for large screens, an eye movement plus a head movement.

Hover queries may be the lowest cost epistemic action using a mouse. Hover queries cause extra information to pop up rapidly as the mouse is dragged over a series of data objects. No click is necessary. Computer programs highly optimized may enable an effective query rate of one per second; however, this rate is only possible for quite specific kinds of query trajectory. We usually cannot jump from point to point in a data space as rapidly using a mouse as we can by moving our eyes.

Clicking a hypertext link involves a 1- to 2-sec guided hand movement and a mouse click. This can generate an entirely new screenful of information, but the cognitive cost is that the entire information context typically has changed. The new information may be presented using a different visual symbol set and different layout conventions, and several seconds of cognitive reorientation may be required.

Compared to eye movements or rapid exploration techniques such as hyperlink following or brushing, navigating a virtual information space by walking or flying is likely to be both considerably slower and cognitively more demanding. In virtual reality, as in the real world, walking times are measured in minutes at best. Even with virtual flying interfaces (which do not attempt to simulate real flying and are therefore much faster) it is likely to take tens of seconds to navigate from one vantage point to another. In addition, the cognitive cost of manipulating the flying interface is likely to be high without extensive training. Also, although walking in virtual reality simulates walking in the world, it cannot be the same, so the cognitive load is higher.

Table 11.1 gives a set of rough estimates of the times and cognitive costs associated with different navigation techniques. When simple pattern finding is needed, the importance of having a fast, highly interactive interface cannot be emphasized enough. If a navigation technique is slow, then the cognitive costs can be much greater than just the amount of time lost, because an entire train of thought can become disrupted by the loss of the contents of both visual and nonvisual working memories.

Table 11.1 *Approximate time to execute various epistemic actions*

Epistemic Action	Approximate Time	Cognitive Effort
Attentional switch within a fixation	50 msec	Minimal
Saccadic eye movement	150 msec	Minimal
Hover queries	1 sec	Medium
Selection	2 sec	Medium
Hypertext jump	3 sec	Medium
Zooming	2 sec + log scale change	Medium
Virtual flying	30 sec or more	High
Virtual walking	30 sec or more	High

Visual Queries

A visual query is the formulation of a hypothesis pertaining to a cognitive task that can be resolved by means of the discovery, or lack of discovery, of a visual pattern. The patterns involved in visual problem solving are infinitely diverse: Pathfinding in graphs, quantity estimation, magnitude estimation, trend estimation, cluster identification, correlation identification, outlier detection and characterization, target detection, and identification of structural patterns (e.g., hierarchy in a network) all require different types of pattern discovery.

For a visual query to be performed rapidly and with a low error rate, it should consist of a simple pattern or object that can be held in visual working memory. In light of studies of visual working memory capacity, it is possible that perhaps only three elementary queries, or one more complex query, can be held in mind. Other cognitive strategies are required when a query is more than the capacity of visual working memory. Figure 11.10 is intended to suggest the kind of complexity that can be involved in a simple visual query. The number of possible query patterns is astronomical, but knowledge about the requirements of rapid visual search can provide a good understanding of the kinds of visual queries that can be processed rapidly. We may be able to query patterns of considerably greater complexity as we become expert in a particular set of graphical conventions. A chess master can presumably make visual queries consisting of patterns that would not be possible for a novice. Nevertheless, even for the expert, the laws of elementary pattern perception will make certain patterns much easier to see than others.

Computational Data Mappings

There is no limit to the variety and complexity of computer algorithms that may be used to transform data into pixels on a computer screen. Such algorithms are part of the overall visual thinking process. Here we are concerned with simple algorithms that

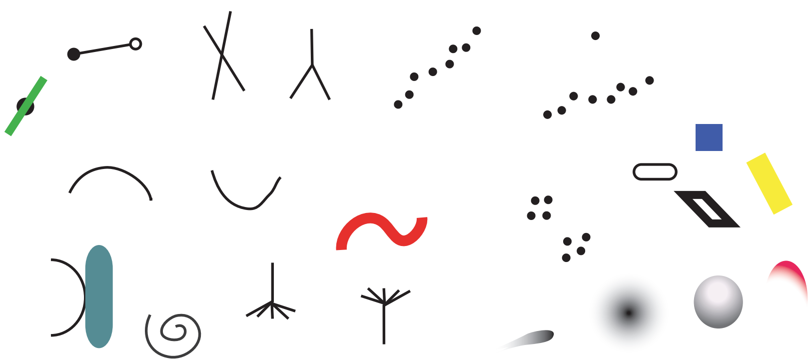


Figure 11.10 Any simple pattern can form the basis of a visual query. Expertise with a particular kind of visualization will allow for more sophisticated visual queries.

change the mapping of the data to the display in a relatively straightforward and rapid way; for example, zooming in on a plane filled with data causes some data to be magnified and some to be excluded from view. More sophisticated algorithms, such as those underlying a web search, are relevant to visual thinking and cognition in general but are too varied and complex to be succinctly characterized.

In interfaces for exploring complex or high-volume data sets, it is important that the mapping between the data and its visual representation be fluid and dynamic, and it is also important that the cognitive effort needed to operate the controls is not so much that there is nothing left over for analysis. Certain kinds of interactive techniques promote an experience of being in direct contact with the data. Rutkowski (1982) calls it the *principle of transparency*; when transparency is achieved, "the user is able to apply intellect directly to the task; the tool itself seems to disappear." Extensive experience is one way of achieving transparency, but good user interface design can make the achievement of transparency straightforward even for novices. There is nothing physically direct about using a mouse to drag a slider on the screen, but if the temporal feedback is rapid and compatible, the user can obtain the illusion of direct control. A key psychological variable in achieving this sense of control is the responsiveness of the computer system. If, for example, a mouse is used to select an object or to rotate a cloud of data points in three-dimensional space, as a rule of thumb visual feedback should be provided within 1/10 sec for people to feel that they are in direct control of the data (Shneiderman, 1987).

Often data is transformed before being displayed. Interactive data mapping is the process of adjusting the function that maps the data variables to the display variables. A nonlinear mapping between the data and its visual representation can bring the data into a range where patterns are most easily made visible. Often the interaction consists of imposing some tranformative function on the data. Logarithmic, square root, and other functions are commonly applied (Chambers et al., 1983). When the display variable is color, techniques such as histogram equalization and interactive color mapping can be chosen (see Chapter 4). For large and complex data sets, it is sometimes useful to limit the range of data values that are visible and mapped to the display variable; this can be done with sliders (Ahlberg et al., 1992).

Visual Thinking Algorithms

We are now ready to bring all the system components together to consider how they are involved in the visual thinking process. The following sections contain a set of nine sketches of *visual thinking algorithms*. The term *algorithm* is usually applied to programs executed on a computer, but it also means any clearly described method or process for solving a problem. In the case of the visual thinking algorithms described here, perceptual and cognitive actions are integrated in a process with a visualization of data. In some examples, computer-based computation is part of the algorithm, although guided by the epistemic actions of the user.

Each of the algorithms is described using pseudocode. Pseudocode is a way of describing a computational algorithm designed for human reading, rather than computer reading. Pseudocode is informal, and these algorithms are only sketches intended to describe visual thinking processes so as to make it clear where they are suitable and offer insights into possibilities for optimization. In addition, a pseudocode description of an algorithm can, in some cases, support calculations that predict the time that will be required to carry out a visual thinking algorithm, and it can show where one method will be an improvement over another.

An important thing to take note of in these algorithms is the interplay between different kinds of information and different kinds of operations, especially the following:

- **Perceptual and cognitive operations.** These include anything occurring in the brain of a person, including converting some part of a problem into a visual query, mentally adding imagery, and mentally adding attributes to a perceived symbol or other feature. Cognitive operations include decisions such as terminating a visual search when an item is found.
- **Displayed information.** This is the information that is represented in a visualization on either a screen or a piece of paper. It could also include touchable or hearable information, although we do not deal with that here.
- **Epistemic actions.** These are actions designed to seek information in some way. They include eye movements to focus on a different part of a display and mouse movements to select data objects or navigate through a data space.
- **Externalizing.** These are instances where someone saves some knowledge that has been gained by putting it out into the world—for example, by adding marks to paper or entering something into a computer.
- **Computation.** This includes all parts of a visual thinking algorithm that are executed in a computer.

Algorithm 1: Visual Queries

Visual queries are components of all visual thinking algorithms. In computer science terms, they can be thought of as subroutines. We will begin by spelling out some of the details of how visual queries work so that later we can just use the term *visual query* as a shorthand way of referring to a complete algorithm.

In a visual query, problem components are identified that have potential solutions based on visual pattern discovery. To initiate a visual query, some pattern is cognitively specified that, if found in the display, will contribute to the solution of a problem. The absence of a pattern can also be a contribution. One example might be where we wish to trace out relationships between data objects using a network diagram. If those data objects are represented by graphical symbols, the first visual query is a search for one of the node symbols. The visual query will be a search pattern based

[A1] Visual queries

Display environment: A graphic display containing potentially meaningful visual patterns.

1. *Problem components are identified that have solutions based on visual pattern discovery. These are formulated into visual query patterns sufficient to discriminate between anticipated patterns.*
2. *The low-level visual system is tuned to be sensitive to the query pattern. Visual information from the display is processed into a set of feature space maps weighted according to the search pattern. A visual scanning strategy is activated based on prior knowledge, display gist, and the task.*
3. *An eye movement is made to the next best target location based on the feature space map, scene gist, and prior knowledge regarding the likely locations of targets.*
4. *Within the fixation, search targets are processed serially at approximately 40 msec per item. Patterns and objects are formed as transitory nexii from proto-object and proto-pattern space. These are tested against the visual query pattern.*
5. *Repeat from 3 as needed.*
   - 5.1 *Only a simple description of object or pattern components is retained in visual working memory from one fixation to the next. These object nexii also contain links to verbal–propositional information in verbal working memory.*
   - 5.2 *A small number of cognitive markers may be placed in a working memory spatial map of the display space to hold task-relevant information when necessary.*

on the shape and size of that symbol. Subsequent visual queries are executed to trace out the lines connecting the end point symbols. These will require the construction of query patterns for pathfinding, and the visual system will be tuned to find linear features having a particular color, connecting endpoints that have been marked in working memory in a visual spatial map.

The visual query algorithm is given in pseudocode in box [A1]. The most important issue in determining how quickly and accurately the algorithm will be executed has to do with whether or not the target pattern is preattentively distinct, a subject that has already been dealt with extensively in Chapter 5. In algorithmic terms, preattentive search is a parallel process, where the entire display is simultaneously analyzed using the low-level feature maps to determine the target location. An eye movement is then executed to confirm the target identity. Visual queries will be fast and error free if the search targets are distinct in terms of the low-level channels of early visual processing. If there is only one target and it is very salient, it will be found in a single eye movement taking perhaps a quarter of a second. If there are several potential candidates, the time will be multiplied by the number of candidates. If the target is not preattentive, every likely symbol must be scrutinized and the time will be much longer. In the worst case, an actual target may be difficult to find because of visually similar nontargets that attract more attention than the actual target. In this case, there will be a good chance that the target pattern will not be found, especially if the visual search is time constrained.

In addition to preattentive distinctness determining the success of a query, a major factor is the skill that some individuals will have gained with a particular kind of display. For an expert, the gist of a very familiar display will trigger particular patterns of eye movements that are most likely to result in a successful search. The expert's brain will also be more effective in the low-level tuning for the visual system needed to find certain critical patterns.

Algorithm 2: Pathfinding on a Map or Diagram

The task of finding a route using a map is very similar to that of finding a path between nodes in a network diagram or between people in a social network diagram. It involves tracing out paths between node symbols. The general algorithm is given in pseudocode in box [A2].

To give substance to this rather abstract description let us consider how the model deals with a common problem—planning a trip aided by a map. Suppose that we are planning a trip through France from Port-Bou in Spain, near the French border, to Calais in the northeast corner of France. The visualization that we have at our disposal is the map shown in Figure 11.11.

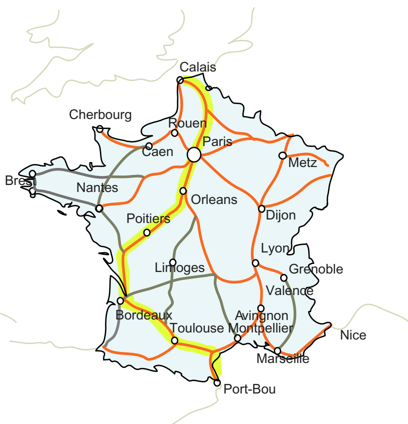


Figure 11.11 Planning a trip from Port-Bou to Calais involves finding the major routes and then choosing between them. This process can be understood as a visual search for patterns.

[A2] Pathfinding on a map or node–link diagram

Display environment: A road map with symbols representing cities and colored lines representing roads between the cities; alternatively, a node–link diagram with symbols representing nodes and colored lines representing links between nodes.

1. *Conduct a visual search to find node symbols representing start and end points.*
2. *Mark these in mental map of display space.*
3. *Fixate the start symbol.*
   - 3.1 *Extract patterns corresponding to connecting lines of a particular color that trend in the right overall direction.*
   - 3.2 *Mentally mark the end point symbol of the best candidate line.*
4. *Repeat from 3 using a new start point until the destination point is located.*
5. *Push information concerning the path to the logical propositional store (only very little is needed because the path can be easily reconstructed).*
6. *Repeat from 3 to find alternative candidate paths, avoiding paths already found.*

The initial step in our trip planning is to formulate a set of requirements. Let us suppose that for our road trip through France we have 5 days at our disposal and we will travel by car. We wish to stop at two or three interesting cities along the way, but we do not have strong preferences. We wish to minimize driving time, but this will be weighted by the degree of interest in different destinations. We might use the Internet as part of the process to research the attractions of various cities; such knowledge will become an important weighting factor for the route alternatives. When we have completed our background research, we begin planning our route using a problem-solving strategy involving visualization.

Visual Query Construction

We establish the locations of various cities through a series of preliminary visual queries to the map (see Algorithm 1). Finding city icons and reading their labels help to establish a connection to the verbal–propositional knowledge we have about those cities. Little, if any, of this will be retained in working memory, but meaningful locations will have become primed for later reactivation.

Once this has been done, path planning can begin by identifying the major alternative routes between Port-Bou and Calais. The visual query we construct for this will probably not be very precise. Roughly, we are seeking to minimize driving time and maximize time at the stopover cities. Our initial query might be to find a set of alternative routes that are within 20% of the shortest route, using mostly major highways. From the map, we determine that major roads are represented as wide red lines and incorporate this fact into the query.

The Pattern-Finding Loop

The task of the pattern-finding loop is to find all acceptable routes as defined by the previous step. The visual queries that must be constructed consist of continuous contours, mostly red (for highways), not overly long, and going roughly in the right direction. Our visual system is only capable of dealing with simple path patterns in visual queries; in this case, these patterns will consist of a single road section connecting two cities, or we may be able to see a path made up of two connected sections, especially if they are short. For the map shown in Figure 11.11 the problem must be broken into components. First a section of road is discovered that trends in the right direction, perhaps the section between Port-Bou and Bordeaux. Next, a visual spatial working memory marker is placed on Bordeaux and a visual query is executed to find the next section of road, and so on, until the destination city is found or the path is abandoned. There are clear limits to the complexity of paths that can be discovered in this way, which is why people resort to externalization for more complex versions of this task, such as actually drawing on the map or enlisting a computer program, such as Google Maps, via epistemic actions to request that it find the best path.

Even in a simple case like that shown in Figure 11.11, a single route, once found, may use the entire capacity of visual working memory. If we wish to look for other routes, this first solution must be retained in some way while alternates are found. Verbal–propositional working memory may be employed by cognitive labeling (e.g., we might remember simply that there is a *western route* or a *Bordeaux route*), and this label can be used later as the starting point for a visual reconstruction if it is needed. The residue from the act of finding the path in the first place ensures that a reconstruction will be rapid.

It should be clear from the above description that a key bottleneck is working memory capacity, in terms of both the complexity of the patterns that can be held and the number of spatial markers available. We can only hold three chunks in visual working memory, which means that when paths are long and complex it may be necessary to use verbal working memory support in addition to visual working memory. The spatial markers that we establish at way points are used to revisit sections of a path and as a low-cost way of holding partial solutions, but only a few of these can be retained. It depends on the complexity of the map (and Figure 11.11 is very simple), but working memory limits suggest that paths of fewer than six or so segments are about the limit for easy visual pathfinding. Perhaps some visual chunking of path components will increase this limit somewhat, especially if the path is repeatedly examined, but where paths to be found are long and winding, with many intersections, computer support should be provided for the pathfinding task.

[G11.2] When designing an interactive node–link diagram or road map, consider providing algorithm support for pathfinding if paths are complex.

The problem of tracing paths in network diagrams is very similar to that of tracing paths on a map. In a social network, for example, the nodes will represent people and the links will represent various types of social connections. The problem of path tracing, though, may be more difficult because in a network diagram the length of the lines has no meaning and paths may cross, especially in dense networks. This means that the visual thinking heuristic of starting with paths that trend in the right direction may not be effective.

Algorithm 3: Reasoning with a Hybrid of a Visual Display and Mental Imagery

Sometimes mental images can be combined with an external diagram to help solve a problem. This enables visual queries to be executed on the combined external/internal image. A simple experiment by Shimojima and Katagiri (2008) illustrates this. They showed subjects a simple block diagram containing blocks labeled A and B, with block A above block B, as shown in Figure 11.12. Next they told the subjects to consider the case of another block, C, that was above block A. Finally, they asked them the question, "Is block C above or below block B?"

This is a simple reasoning task that could be carried out using logic and the rule of transitivity which applies to relative height. If (A > B) and (C > A) it follows that (C > B). But, in fact, they appeared to solve the problem perceptually. The experiment was carried out using equipment to monitor subjects' eye movements, and it was found that when subjects were asked to perform this task they looked up into the

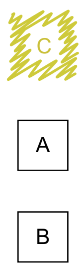


Figure 11.12 Blocks A and B are drawn on the paper. The yellow irregular line represents an imagined block, C.

Figure 11.13 The imagined (yellow) additions to the parallelogram suggest a method for calculating the area of a parallelogram.

blank space above block B as if they were imagining a block there. They were acting as if they could "see" block C above block A. In their imagination they could also see that block C was above block B. In other words, they solved the problem using a percept that was a hybrid of external information from the display with a visually imagined addition.

Another example comes from Wertheimer (1959), who studied children solving geometric problems. The children were asked to find a formula that could be used to calculate the area of a parallelogram. They already knew that the area of a rectangle is given by the width multiplied by the height, and they were given the drawing shown in Figure 11.13. To solve this problem some of the students mentally imagined extra construction lines and were (according to Wertheimer) able to perceive a solution by examining the combined mental and actual image. They noticed that the parallelogram could be converted to a rectangle if a triangle were cut off from the right and placed on the left. This gave them the answer—the area of a parallelogram is also given by the width of the base times the height.

[A3] Reasoning with a display and mental imagery

Display environment: A diagram or other visualization representing part of the solution to a problem.

1. *Perceive task-relevant patterns in the display and mentally add semantic attributes.*
2. *Mentally image an addition to the display that will help with the visual reasoning process.*
3. *Execute visual queries on the combined internal/external image to solve the problem.*

The addition of mental imagery to external imagery has a great many variations, and box [A3] gives only the most basic form of this algorithm. One of its limitations is our ability to mentally imagine additions to visualizations, and this is extremely restricted, at least for most people (Kosslyn, 1990). Because of this, much of the most flexible and creative visual thinking involves externalizing tentative solutions. This is called *creative sketching*, and we deal with it next.

Algorithm 4: Design Sketching

Sketching on paper, a blackboard, or a tablet computer is fundamental to the creative process of most artists, designers, and engineers. There is a huge difference between creative sketching and the production of a finished drawing. Creative sketches are thinking tools primarily composed of rapidly drawn lines that are mere suggestions of meaning (Kennedy, 1974; Massironi, 2004), whereas finished drawings are polished recordings of ideas that have already been fully developed.

Sketches can be considered as externalization of mental imagery. Someone who begins a sketch is literally trying to represent on paper something he has imagined. Because of the limitations of visual imaging (Kosslyn, 1990) what can be mentally imaged is quite simple. If something, however crude, that represents a mental image can be put down as a sketch, then additional elements can be mentally imaged as *additions* to what is already on the paper.

Sketches benefit from the abstract nature of lines. A line can represent an edge, a corner, or the boundary of a color region, as well as something quite abstract, such as the flow of people in a large store. Lines on the paper can be reinterpreted to have different meanings. A scribbled area on the sketch of a garden layout can be changed from lawn to patio to vegetable garden, simply by an act of imagination. The psychologist Manfredo Massironi (2004) invented an exercise that dramatically illustrates the ease with which the brain can interpret lines in different ways. First draw a scribble on a piece of paper—a single line with three or four large loops should be sufficient. Next, try to turn the scribble into a bird simply by adding a "<" and an "o." In a surprising

[A4] Design sketching

Display environment: Paper and pencil or tablet computer.

1. *Mentally image some aspect of a design.*
2. *Put marks on display to externalize aspects of the imagined design.*
3. *Construct analytic visual queries to determine if design meets task requirements.*
4. *If a major flaw is found in the design as represented that cannot be easily fixed (by erasure or other graphical correction), discard sketch.*
5. *Mentally image design additions to the sketch and/or mentally reattribute the meaning of particular lines and other marks.*
6. *Execute visual queries to critically assess the value of mentally imaged additions in the context of existing sketch.*
7. *If mental additions are perceived as valuable, externalize by adding marks or by erasures.*
8. *Repeat from 5, revising the sketch, or discard the sketch and begin from 1.*

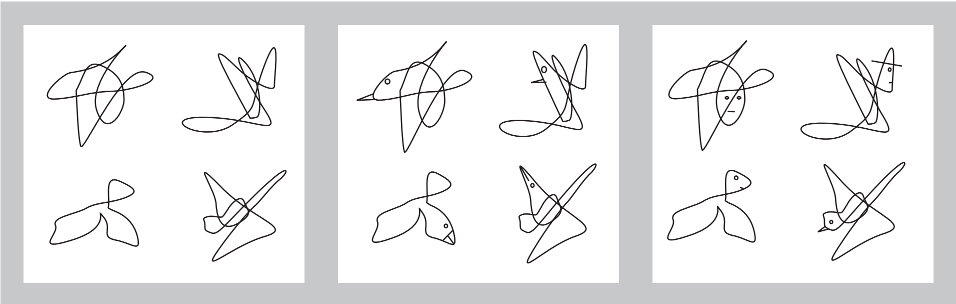
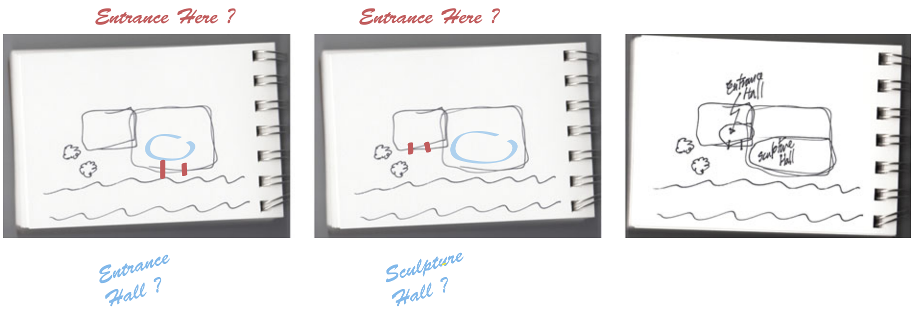


Figure 11.14 The metamorphosis of scribbles. (*From Ware (2009), based on a concept by Massironi (2004). Reproduced with permission.*)



(a) (b) (c)

Figure 11.15 (a) The entrance is imagined on the right. (b) An alternative is imagined with an entrance on left. (c) The solution is externalized.

number of instances, the meaningless loops will become resolved into heads and wings and very satisfactory birds will result (see Figure 11.14).

The creative sketching algorithm is set out in box [A4]. It involves a cycle in which concepts are externalized through marks on paper, then interpreted through analytic visual queries. Additions or deletions are mentally imaged so as to provide a low-cost way of testing new concepts in the context of those already set down. Those that pass the test will result in new externalizations. Sketches themselves are disposable; starting over is always an option.

Architects are known to be prolific sketchers, and Suwa and Tversky (1997) studied how they used sketches in the early stages of design. They found that a kind of analytic seeing was important and that there were often unintended consequences resulting from the placement of sketch lines. Sometimes these resulted in constructive solutions that had not been noticed previously.

An example of how sketching might be used in an architectural design project is given in Figure 11.15. The site constrains the basic footprint of the building to the two rectangles that have been roughly scribbled, as shown in Figure 11.15(a). The architect next imagines the main entrance in the center of the large rectangle, shown in Figure 11.15(b), but immediately realizes that the space needed for an entrance hall and its associated ticket offices will conflict with the client's wish to have a great sculpture hall with windows looking out in that direction. The architect next imagines the entrance and entrance hall in the smaller rectangle and, because this works better, adds lines to externalize the concept.

For creativity to be supported, the medium used for design must afford tentative interactions. The lack of precision in quick, loose sketches actually allows for multiple interpretations. The sketches that people construct as part of the creative process are rapid, not refined, and readily discarded. Giving a child high-quality watercolor paper and paints is likely to inhibit creativity if the child is made aware of the expense and cautioned not to "waste" the materials. Schumann et al. (1996) carried out an empirical study of architectural perspective drawings executed in three different styles: a precise line drawing, a realistically shaded image, and a sketch. All of the drawings contained the same features and level of detail. The sketch version was rated substantially higher on measures of ability to stimulate creativity, changes in design, and discussions.

Algorithm 5: Brushing

It is often useful to represent data in several different views. Figure 11.16 is a complex display showing a graph of crime plotted against income level, a map view of crime statistics, a table view of more detailed numbers, and a histogram. Each of these views provides a different way of looking at the same set of numbers and each has

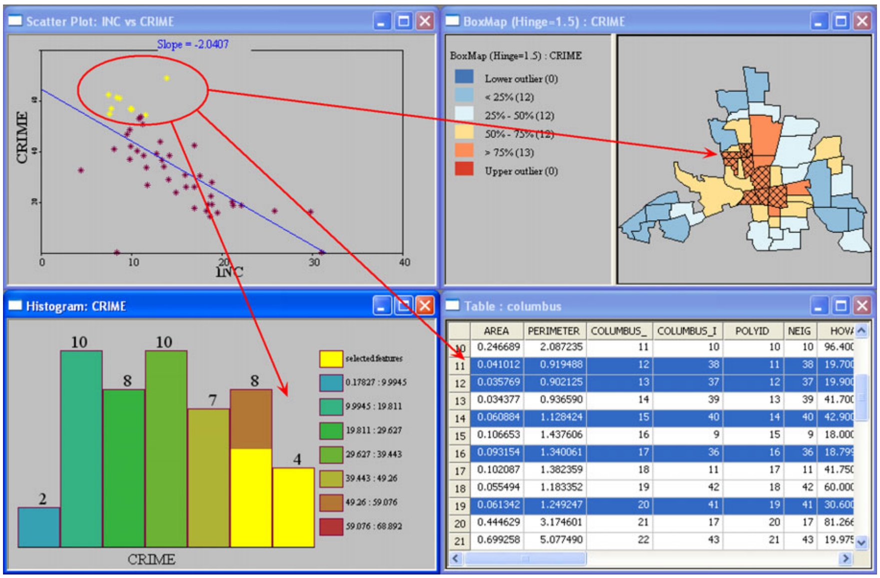


Figure 11.16 The same data is displayed in four different ways, using a scatterplot, a histogram, a map, and a table. Selecting points in one view causes them to be highlighted in all other views. (*Courtesy of Dr. Mike de Smith (http://www.spatialanalysisonline.com/).*)

advantages, but what if we want to relate patterns revealed in the scatterplot to locations on the map? This is a problem that can be solved by a method called *brushing* (Becker & Cleaveland, 1987). In brushing, selecting a data object in any one of the views causes those same data objects to be highlighted wherever they appear in all of the other views. The brushing algorithm is given in box [A5].

[A5] Brushing

Display environment: Data entities are represented in at least two different ways on different parts of the screen or on multiple screens.

1. *Construct a visual query requiring information about a particular subset of the underlying data.*
2. *Select symbols representing the relevant subset of the data. As a result, the computer highlights all other representations of the data that has been selected.*
3. *Execute visual queries for task-relevant patterns in the highlighted representations. The queries may require information from two or more representations and be limited by visual working memory capacity.*

The goal of the brushing is to allow users to relate information patterns in one part of a compound display with patterns in another part. Information about those patterns must be stored in working memory (either visual or verbal) while attention is transferred. If the transfer of attention requires a visual search of even a few seconds, this can cause substantial loss of the working memory information and greatly reduce overall cognitive efficiency. For this reason, it is clearly essential that highlighting methods should support a rapid visual search.

A common problem is that composite displays of this kind are almost always visually complex; they are likely to already use a variety of line styles, colors, and textures, and this makes finding a visually distinctive highlighting method challenging. One solution is to use motion highlighting, assuming that motion is not already used in the data coding (Bartram & Ware, 2002). Motion has the advantage that it works well in the periphery of vision and it interferes little with the perception of color and shape.

Algorithm 6: Small Pattern Comparisons in a Large Information Space

A need to see detail in a larger context is a common problem for data visualization. The most common example is a map display, where we wish to compare small-scale features on the map. But, the same problem occurs with more abstract data, such as large network diagrams.

To solve this focus and context problem many systems afford epistemic actions that provide the user with a method for moving attention easily between detail and context views. In the previous chapter, we discussed zooming, adding extra linked windows, and other methods as a problem of mental geometry and found that some transformations are easier than others. In most cases, though, a much more important constraint on cognitive performance is imposed by visual working memory capacity.

To help analyze the problem of which focus and context interface is likely to be best we will take as a model the task of comparing patterns that are isolated small islands of information in a large geographical space. This is illustrated in Figure 11.17. The figure shows extra linked windows, placed so as to show two areas of detail.

A simpler alternative to having extra windows is a straightforward zooming interface. With a zooming interface, comparisons are made through rapid scale changes. The user must zoom in and look at one area of detail, hold the pattern (or part of it) in visual working memory, zoom out to get an overview and seek another pattern, and then zoom in again to make a comparison. The pattern in visual working memory

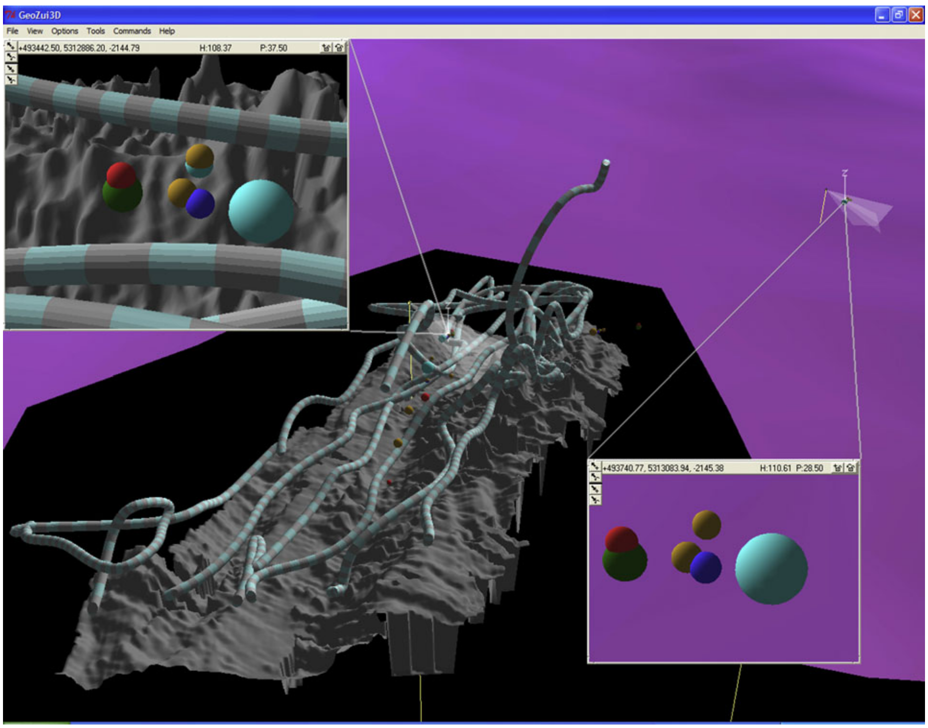


Figure 11.17 Subwindows allow details to be compared while the overall context can also be seen (GeoZui3D interface).

is compared to new patterns found during the search process. If a possible match is found, it may be necessary to zoom in and out and back and forth to confirm details.

With the use of extra windows, as shown in Figure 11.17, parts of the main display are magnified. When two such windows are in position, it is possible simply to make eye movements between them to assess the relationship more rapidly.

The general algorithm for this task is given in box [A6]. It involves moving back and forth between patterns to make comparisons. This movement is an epistemic action that depends on the interface that has been provided. One way of implementing the epistemic action is through an interface that makes zooming rapid and easy. Another way is to provide support for extra magnifying windows. If two extra magnifying windows are used, they must be set up over pairs of patterns to make the comparison, but when the windows are in place the visual comparison can be made with much more rapid eye movements (Plumlee & Ware, 2002).

The critical resource here is visual working memory capacity, because this determines how many visits, back and forth, are required to make a comparison between a pair of patterns. If the master pattern is simple enough to be held in visual working memory, then zooming will often be more efficient, because it avoids the overhead of setting up multiple windows. If more than three visual-working-memory-sized chunks are in the master pattern, then it will be necessary to zoom back and forth between them, and the multiwindow solution will be faster.

[A6] Small pattern comparisons in a large information space

Display environment: A large data space with small isolated patterns that must be compared in some way.

1. *Execute an epistemic action by navigating to the location of the first pattern.*
2. *Retain a subset of the first pattern in visual working memory.*
3. *Execute an epistemic action by navigating to the candidate location of a comparison pattern.*
4. *Compare the working memory pattern with part of the pattern at the candidate location.*
    - 4.1 *If a suitable match is found, terminate the search.*
    - 4.2 *If a partial match is found, navigate back and forth between the candidate location and master pattern location, loading additional subsets of candidate pattern into visual working memory and making comparisons until a suitable match or a mismatch is found.*
5. *If a mismatch is found repeat from 1, cognitively marking candidate locations that have already been evaluated.*

In its simplest form, the time taken to perform this task is given by:

$$\text{Time} = \text{setup\_cost} + \text{number of comparison queries}$$

The number of comparison queries depends on the number of visual chunks in the patterns to be compared and on visual working memory capacity; for example, if there are seven visual chunks to be compared, the number of comparison queries will be three, because only three chunks can be stored in visual working memory to make a comparison. The first and second comparisons will involve three chunks each and the last will involve one chunk.

Plumlee and Ware (2002) modeled and predicted user performance on this task with the two interfaces we have been discussing—simple zooming vs. multiple windows. The number of zooms vs. window movements necessary to complete the task of finding identical clusters of simple shapes widely separated in a geographical space was estimated. Visual working memory was considered as a critical resource. The predictions of the model are shown in Figure 11.18 (left), modeled for capacities of visual working memory at two, three, and four items, leading to a range of predictions as shown by the broad colored wedges. When there are fewer visual chunks in the patterns to be compared, the zooming interface is best. As the number of chunks increases, the extra window interface is better. The crossover should be at about three chunks. The measured results, shown Figure 11.18 (right), closely matched the prediction.

The model we have been describing here is greatly simplified. In fact, because eye movements have such a low cost, people act as if they are only comparing one object at a time (instead of three) with the multiple windows interface. They make many

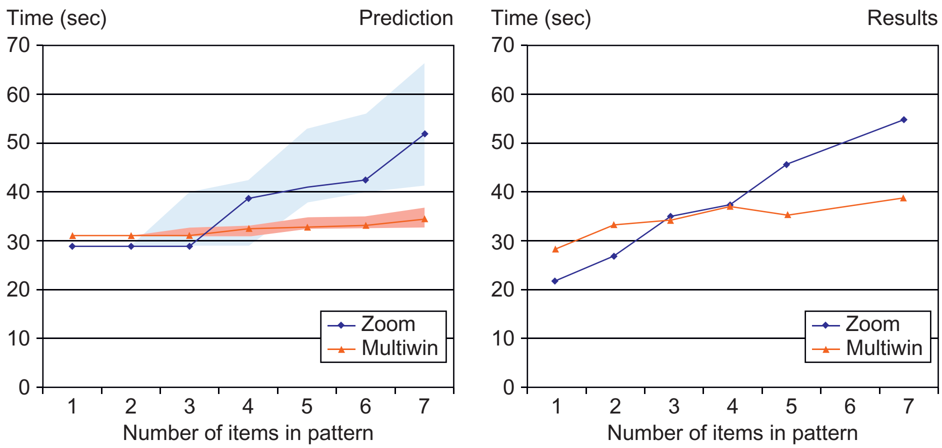


Figure 11.18 Model predictions are shown on the left. Measured task performance is shown on the right. Multiple windows speed performance relative to the use of a zooming interface when the number of objects to be compared is five or more.

more eye movement than necessary and they also make far fewer errors (Plumlee & Ware, 2006). So the multiwindow solution is more reliable as well as faster.

Still, in many cases, detailed modeling is not necessary to decide if a user interface should support extra windows for detailed pattern comparisons. We can give the following rule of thumb:

> **[G11.3]** In large data spaces containing small islands of critical information, consider enabling the user to add extra windows showing magnified areas of the larger space. This is especially useful for tasks that require frequent queries to compare patterns having more than three visual working memory chunks. This is a supplement to guideline G10.15.

Algorithm 7: Degree-of-Relevance Highlighting

Sometimes information objects in a display are interrelated in ways that are highly task relevant. If we inquire about a particular data object—say, a node representing a man who is a criminal suspect—then we also likely want to know about his known associates. Normally, the designer will group these related objects on the screen, but this is not always possible because of other design constraints, so related objects become distributed across the display. Also, there are many cases where the amount of information is such that a simplified representation of every data object can be placed on the screen but not with adequate clarity or detail.

In *degree-of-relevance highlighting*, we are interested in displaying all of the information on the screen at once, but because of its density it cannot all be made legible. A simple interaction solves the problem; touching an object causes both it and other task-relevant data objects to be highlighted, and the highlighted objects may also reveal additional detail. Degree of relevance is calculated using a computer algorithm designed to rate the task relevance of other entities in the database based on interaction history. The simplest version of this involves only the most recent selection.

One way that this approach has been employed is in network diagrams consisting of nodes and links. Most static diagrams contain fewer than 30 or so graphically represented entities and a similarly small number of lines linking or enclosing them. Having too many nodes and links makes it impossible to trace out the connections between them. Degree-of-relevance highlighting makes it possible to deal with much larger diagrams.

The *Constellation* system of Munzner et al. (1999) provides an example of how interactive degree-of-relevance highlighting can provide views into a very complex semantic network, far larger than can be displayed with static concept maps. Figure 11.19 shows a screen shot, but this static image does not do justice to the system. Constellation uses hover queries to allow for rapid highlighting of subsets of the graph. Links attached to a node become highlighted as the cursor passes over the node. In addition,

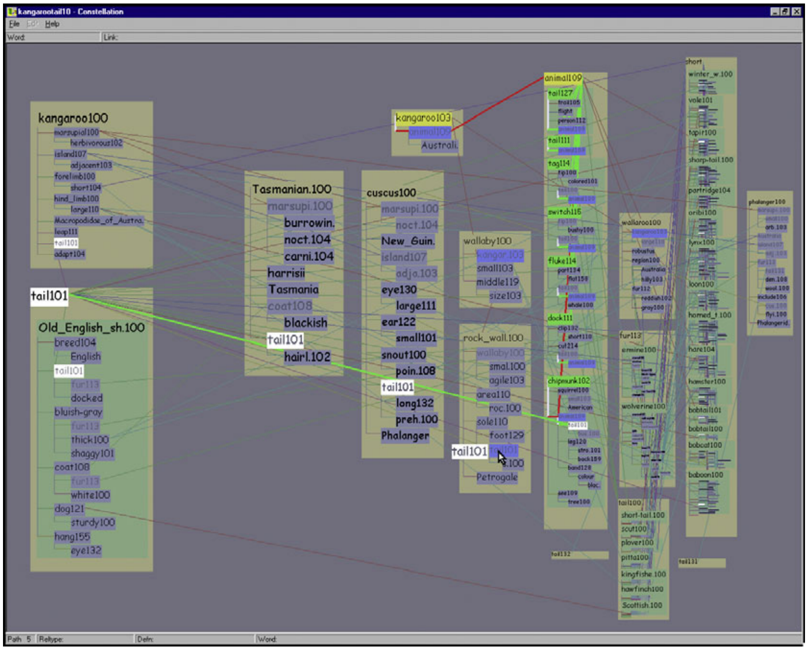


Figure 11.19 A screen image of the Constellation system (Munzner et al., 1999) showing a view into the MindNet semantic network database. (*Reproduced with permission.*)

when the user clicks on a particular node, closely related semantic concepts are allocated more screen space and larger fonts. In essence the computer provides a *visual information scent*, to use Pirolli and Card's (1995) term, as a guide to the best place to search for more information. By using this technique, a large amount of semantic information can be accessed very quickly.

Note that the rapid query techniques get around the usual problems of graph layout. Most of the work in graph layout is aimed at producing aesthetically pleasing drawings of graph structures by paying particular attention to minimizing edge crossings of nodes (Di Battista et al., 1998). A clear static graph drawing of the information in Figure 11.19 is probably impossible, because there are simply too many links. In Constellation, Munzer abandoned the usual criteria, allowing edges to cross each other and to cross nodes, using interactive techniques to reveal information as needed allowed visual access to much larger structures.

The MEgraph system is another example of degree-of-relevance highlighting (Ware & Bobrow, 2005; Ware et al., 2008). MEgraph used Fortune 500 companies as a test example, illustrated in Figure 11.20. This graph is actually a kind of social network, showing links between companies (colored dots) via members of the boards of directors (gray dots) for those companies. When board members are on the boards of more than one company, they form a high-level social link between the companies. In MEgraph, touching a node causes *motion highlighting* of the social links between nodes

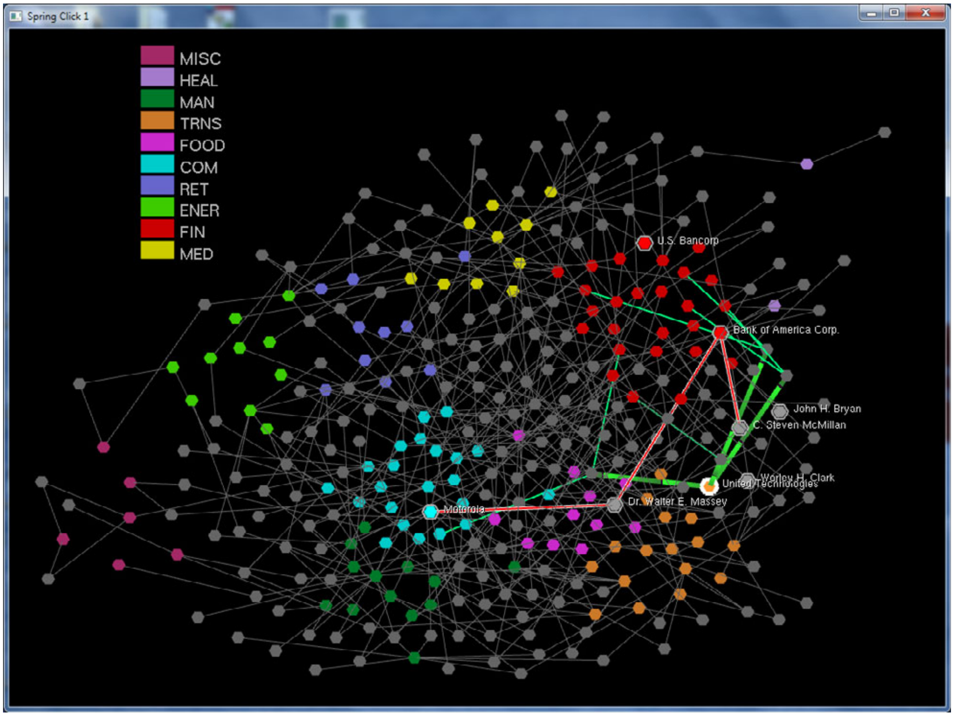


Figure 11.20 The MEgraph system uses motion as additional highlighting on the green lines and their attached nodes. This makes them independently searchable.

and the labels of the companies to appear. Users can choose to set the range of highlighting at one link, two links, or more. The reason why this approach makes sense is that in social networks we are mostly interested in short chain connections, making degree of relevance easy to compute—for example, who is a friend and who is a friend of a friend? Rarely is a chain longer than that; therefore, automatically highlighting these short chains will help users reason with the diagram.

The degree-of-relevance highlighting algorithm is given in pseudocode in box [A7]. On average, the time taken to find a target on a single iteration of the main loop is given by

$$MeanTime = p_h \times t_h + p_{nh} \times t_{nh} \tag{11.1}$$

where p_h is the probability that the search target is in the highlighted set, and t_h is the time taken for the visual search. This can be very short if the target is a member of a small preattentively distinct set, but typically would not take more than a few seconds even if a serial search is needed. p_{nh} is the probability of finding the target when it is *not* highlighted, and t_{nh} is the time required to find that target. If a target is not highlighted, the search time may be much longer, perhaps by minutes, and so the value of the algorithm depends on how efficient the computer can be at finding task-relevant information.

[A7] Degree-of-relevance highlighting

Display environment: A display containing many symbols representing entities linked by a complex overlapping set of relationships.

1. *Construct a visual query to find a symbol that may lead to useful information (information scent).*
2. *Execute an epistemic action by selecting a symbol.*
3. *Computer highlights all symbols with a high degree of relevance to selected symbol.*
4. *Execute a visual pattern query among highlighted symbols for additional information scent.*
5. *If a very high relevance symbol is found, execute an epistemic action to drill down for additional information. Usually this will be presented in a different display window.*
6. *Repeat from 1 as needed, cognitively marking visited symbols.*

Generally speaking, degree-of-relevance highlighting is useful to display data sets having between 30 and a few thousand entities. There is an upper limit on how much information can be represented on a screen. For example, it may take 100 pixels to draw a symbol, and for clarity a 5-pixel border may be required. This means that, given a 1-million pixel screen, we can represent at most 2500 symbols in a dense matrix, which is far too many to search efficiently. Searching that is not preattentive requires 40 msec per item, plus a 100-msec eye movement, for every 4 or 5 items, meaning that it will take minutes to conduct a visual search for a single symbol without some visual support. If a degree-of-relevance algorithm can reduce the visual search to around 10 to 20 items, then the gain in cognitive efficiency can easily be an order of magnitude.

Algorithm 8: Generalized Fisheye Views

A fisheye view is a display of an information space that has been geometrically distorted to show certain information larger and more clearly while shrinking other information. A *generalized fisheye view* is a much more powerful and abstract concept developed by George Furnas in one of the most influential papers published in the field of information display (Furnas, 1986). In a generalized fisheye view, the computer attempts to show only task-relevant information and hides or shrinks other information. The concept has nothing to do with geometry. Furnas called the function underlying what is shown a *degree of interest (DOI) function*. We will use the term *degree of relevance* instead, because it is useful to focus on task relevance when analyzing algorithms and because the interest of the user is much more difficult to determine.

A closely related concept is the *adaptive level of detail* display (Bishop & Tipping, 1998). In a level of detail display, information is assumed to be hierarchical so that an object can be expanded to expose ever greater amounts of detail. If a display system is adaptive, this means that the system automatically shows more detail for objects that are judged, according to some computational model, to be more task relevant. In general, an adaptive information visualization is any display that adapts based on some computer model of the user's information needs.

[A8] Generalized fisheye views

Display environment: A set of symbols representing data entities drawn from a much larger set. The entities are linked by a complex overlapping set of relationships.

1. *Construct a visual query to find information that may be accessed via a particular symbol (information scent). Conduct a visual search for the symbol.*
2. *Execute an epistemic action by selecting a symbol.*
3. *Computer displays all symbols representing data above computed relevance threshold.*
    - 3.1 *Symbols may be weighted by relevance so that the most relevant are most salient and displayed with most detail.*
    - 3.2 *Symbols with a low computed relevance are hidden.*
4. *Construct a visual query to find information in the updated display.*
5. *If a very high relevance symbol is found, execute an epistemic action to drill down for additional information. Usually this will be presented in a different display window.*
6. *Repeat from 1 as needed, mentally marking locations of visited symbols.*

The algorithm for visual thinking with a generalized fisheye view is very similar to that for degree-of-relevance highlighting. The important difference is that in a generalized fisheye view less important information is completely hidden rather than being merely de-emphasized (as in box [A7]). The generalized fisheye view algorithm is given in box [A8]. On average, the time taken to find a target on a single iteration is given by

$$MeanTime = p_d \times t_d + p_{nd} \times t_{nd} \tag{11.2}$$

where p_d is the probability that the search target is displayed on the screen, and t_d is the time required for the visual search in that case. This can be very short if the target is a member of a small preattentively distinct set, but typically would not take more than a few seconds even if a serial search is needed because the algorithm has reduced the number of displayed objects to a small subset. Also, p_{nd} is the probability of finding the target when it is not on the screen, and t_{nd} is the time to find that target.

As with degree-of-relevance highlighting, the value of the generalized fisheye view algorithm depends entirely on the reliability with which the computer can predict the user's information needs. Sometimes this is easy; for example, a user alert to a system problem may always be followed by a request from the system user for more detailed information about the originating component. If the system can automatically show that extra detail, work will become more efficient.

The downside of generalized fisheye views is that the algorithm will hide important information. Often the user's goals cannot be easily inferred from their actions, and hiding the wrong information can have serious consequences. It may require a whole set of epistemic actions through menu selections, keyword searches, or other navigation methods to find what it needed. This can take an arbitrarily long time, so the success of adaptive level of detail methods obviously depends almost entirely on the success of the degree-of-relevance algorithm in keeping p_{nd} low.

One application of generalized fisheye views is in the adaptive display of large node–link diagrams (Schaffer et al., 1993; Bartram et al., 1994). In their intelligent zoom system (illustrated in Figure 11.21), a hierarchical network diagram is being examined. As parts of the network are expanded to see more detailed connections within components, other parts become more compact. If the user starts to explore other parts of the network, some of the boxes that had previously been opened will be closed to make room, hiding their contents.

Algorithm 9: Multidimensional Dynamic Queries with Scatter Plot

With multidimensional discrete data, all entities have the same set of attributes. The attributes define the data dimensions, and each entity can be thought of as a point in a multidimensional space. For example, a researcher interested in heart disease might have a data set from cardiac patients including measurements of blood chemistry, as well as statistics on blood pressure, alcohol intake, and other variables for every patient. Each measurement defines a data dimension, and each patient becomes a point in a multidimensional space defined by the dimensions. Techniques discussed previously such as enhanced scatterplots or parallel coordinates can be used to display the data, but if the data set is large it will be impossible to visualize in its entirety.

Ahlberg et al. (1992) developed an interface that enables a researcher to narrow down the set of points that is displayed using a set of sliders, one for each data dimension. Each slider adjustment is an epistemic action, narrowing the range of what is displayed. They called the interactive hiding and revealing of data in this way *dynamic queries*, and they demonstrated it with a number of interactive multivariate scatterplot

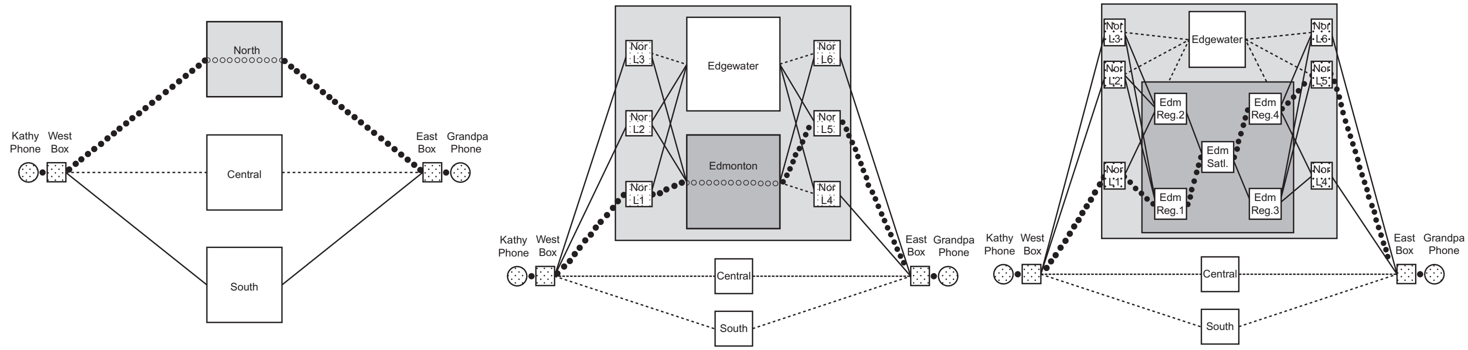


Figure 11.21 A series of frames showing the intelligent zoom interface. Areas of interest expand when selected; other objects shrink accordingly. (*Redrawn from* Schaffer et al. (1993).)

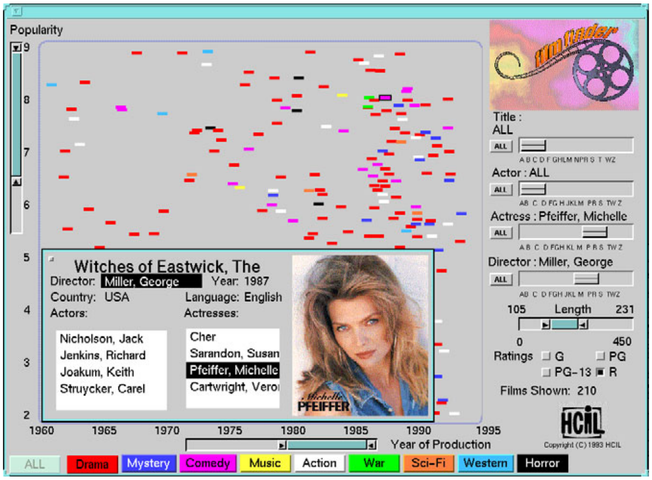


Figure 11.22 The FilmFinder application of Ahlberg and Shneiderman (1994) used dynamic queries to allow rapid interactive updating of the set of data points mapped from the database to the scatterplot display in the main window. (*Courtesy of Matthew Ward.*)

prototypes. It also became the basis for the Spotfire® product. Figure 11.22 shows an example of it in the form of the FilmFinder demonstration application. This provides the user with a slider to select on the basis of movie length, another to select on the basis of year of production, and more to select actor and director names.

The basic algorithm for multidimensional dynamic queries with a scatterplot is given in box [A9]. It involves epistemic actions using interactive slider bars to narrow down the displayed subset of the data space in order to find a small set of symbols that represent the most relevant data. The goal is to reduce the number of displayed points to a manageable size. At this point, a visual pattern search can be made for critical patterns. Ultimately, each of a small set of points may be individually selected to get complete detailed information by means of additional epistemic actions.

We can roughly estimate the size of the database for which this method is useful. The sliders tend to be quite short, because of limitations in available screen space, and this limits the amount of selection that can be imposed. Perhaps, as a rule of thumb, each slider enables us to restrict the search to 10% of the targets on a particular dimension. This means that the overall restriction on what is displayed is 0.1^d, where d is the number of data dimensions. If there are four dimensions, the reduction in the number of targets will be a factor of 10,000.

There are also limitations on the number of sliders that can be meaningfully used before the fluidity of the process becomes compromised. Let's put this limit, arbitrarily, at 10. In addition, let's assume that we would like fewer than 10 targets remaining on the screen at the end of the interactive process as candidates for detailed examination. In this extreme example, a data set containing 100 billion items might be dealt with interactively.

As a final observation, there is no reason why interactive range selection has to be coupled only with scatterplots. The same visual thinking algorithm applies to parallel coordinates, where the sliders are placed directly on the parallel axes (Inselberg & Dimsdale, 1990). Also, interactive range selection using a slider can be applied to any other visualization where it is desirable to restrict what is shown according to some continuously varying attribute.

[A9] Multidimensional dynamic queries with scatterplot

Display environment: A scatterplot with symbols representing entities drawn from a set of multidimensional discrete data, with a set of controls that restricts the range displayed on each of the data dimensions.

1. *User constructs task-relevant visual query that can be addressed by viewing a subset of multidimensional discrete data defined by a hyperbox.*
2. *Execute visual query on scatterplot display.*
    - 2.1 *Is the number of targets small enough to make more detailed visual analysis feasible?*
    - 2.2 *Is the pattern found?*
3. *If a very high relevance symbol is found, execute an epistemic action to drill down for additional information. Usually the results will be presented in a different display window.*
4. *Execute an epistemic action to change the displayed subset by dragging a slider that causes the computer to adjust a range on a data dimension.*
5. *Repeat from 2 until either task is successfully completed or abandoned.*

Algorithm 10: Visual Monitoring Strategies

Supervisory control is a term used to describe a situation where a semiautonomous system, such as a plane on autopilot or a chemical plant, runs with only occasional input from a human operator. In supervisory control systems, operators must monitor a set of instruments every so often. The basic visual thinking algorithm involves a user setting up a schedule of self-interrupts, according to which they will periodically stop whatever else they are doing and conduct a visual scan of a set of displays looking for anomalous patterns that may require action. Once such a pattern is found the appropriate action is taken.

> ***[A10] Visual monitoring strategies***
>
> *Display environment: A set of glyphs representing the status of various system components.*
>
> 1. *Set up a cognitive self-interrupt schedule.*
> 2. *When an internal cognitive interrupt occurs, scan display components with eye movements.*
>   - 2.1 *For each display component, execute visual queries to test for patterns requiring action.*
> 3. *If an actionable pattern is found, take required action.*
> 4. *Repeat from 2 as needed.*

Models developed to account for operators' visual scanning strategies generally have the following elements (Wickens, 1992):

Channels. These are the different ways in which the operator can receive information. Channels can be display windows, dials on an instrument panel, or nonvisual outputs, such as loudspeakers (used for auditory warnings). (Note that this meaning is different from the concept of perceptual channels discussed in this book.)

Events. These are the signals occurring on channels that provide useful information.

Expected cost. This is the cost of missing an event. System operators base their monitoring of different channels on a mental model of system event probabilities and the expected costs of these (Moray & Rotenberg, 1989; Wickens, 1992). Charbonnell et al. (1968) and Sheridan (1972) proposed that monitoring behavior is controlled by two factors: the growth of uncertainty in the state of a channel (between samples) and the cost of sampling a channel. Sampling a channel involves fixating part of a display and extracting the useful information. The cost of sampling is inversely proportional to the ease with which the display can be interpreted. This model has been successfully applied by Charbonnell et al. (1968) to the fixation patterns of pilots making an instrument landing.

Two other factors may influence visual scanning patterns:

Operators may minimize eye movements. The cost of sampling is reduced if the points to be sampled are spatially close. Russo and Rosen (1975) found that subjects tended to make comparisons most often between spatially adjacent data. If two indicators are within the same effective field of view, this tendency will be especially advantageous.

> ***There can be oversampling of channels on which infrequent information appears*** (Moray, 1981). This can be accounted for by short-term memory limitations. Because it requires significant cognitive effort to keep a particular task in mind, people can reliably monitor an information channel on a frequent self-interrupt schedule (e.g., every minute), but they are much less reliable when asked to monitor an event every 20 minutes, presumably because the self-interrupt program is lost from working memory. To compensate, operators may sample more frequently than required.

One solution that can assist system operators in being more reliable is for a computer system to provide visual or auditory reminders at appropriate intervals as an alternative to internal mental interrupts. In addition, if a system can determine when additional attention from an operator is needed this can be signaled. One good way of doing this is to use motion cues, since motion in the periphery of vision is readily detected and different levels of urgency can be expressed (Ware et al., 1992).

The limits of attention and visual working memory capacity mean that well-designed monitoring procedures can break down under extreme conditions. Operators may exhibit dysfunctional behaviors in high-stress situations. Moray and Rotenberg (1989) suggested that under crisis conditions operators cease monitoring some channels altogether. In an examination of control room emergency behavior, they found that under certain circumstances an operator's fixation would become locked on a feedback indicator, waiting for a system response at the expense of taking other more pressing actions.

Conclusion

The ten visual thinking algorithms set out in this chapter are greatly simplified sketches developed to encourage thinking about cognitive tool design in a more process-orientated way. They do not spell out every mouse click or working memory operation. Other methods have been developed that are much more complete and detailed. In particular, the ACT-R model (Anderson et al., 1997) can be used to create a more complete account of the visual and cognitive operations involved in performing particular tasks. But, the cost of using a system like ACT-R is the effort involved in setting up a very detailed cognitive model of task execution. This can take days or weeks, and the process is incompatible with rapid prototype development, a method that usually produces the best designs. The alternative offered here in the form of visual thinking algorithms is intended to provide a framework for rough and ready calculations that can be done in minutes on scraps of paper. This can be done as part of prototype development in order to understand the critical bottlenecks restricting cognitive productivity.

Once we begin to think in terms of visual thinking algorithms it becomes clear that a common bottleneck in cognitive processing comes from the limitations of working memory capacity. This is the reason why it is so essential to enable people to rapidly move attention from one meaningful pattern to another. If we could hold more in our heads, we would not need to shift attention so often. Providing interactive methods that work around the limits of working memory capacity can, in many cases, result in impressive gains in efficiency. For example, adding extra windows for comparing patterns side by side using rapid eye movements instead of slow zooming can provide very substantial gains (Algorithm 6). Degree-of-relevance highlighting means that a network diagram ten times as large can be handled on a single screen (Algorithm 7). Without it, some other method would have to be used, such as zooming, and this would greatly increase both the time and the working memory load.

As a final comment, the person who wishes to design an interactive visualization must contend with two sets of conflicting forces. On the one hand, there is the requirement for the best possible visual solution, tailored exactly to the problem to be solved. On the other hand, there is the need for consistency in representation and interaction style. This need is even greater when large, international organizations have a common set of goals that demand industrywide visualization standards. At the stage of new discoveries in information visualizations, standardization is the enemy of innovation and innovation is the enemy of standardization. It is important that we get the research done before the standards are formed; otherwise, it will be too late. These are exciting times for information visualization, because we are still in the discovery phase, although this phase will not last for long. In the next few years, the wild inventions that are now being implemented will become standardized. Like clay sculptures that have been baked and hardened, the novel data visualization systems of today's laboratory will become cultural artifacts, everyday tools of the information professional.

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APPENDIX A

Changing Primaries

This appendix describes the operation of transforming one set of primaries into another. The mathematical name for this operation is a *change of basis*.

To convert a color from one set of primary lights to another, it is first necessary to define a conversion between the primaries themselves. We can think of this as matching each of the new primary lights using the old primary system. Suppose we designate our original set of primaries P_1, P_2, and P_3 and the new set of primaries Q_1, Q_2, and Q_3. We now use our original primaries to create matches with each of the new primaries in turn. Let us call the amount of each of the P primaries c_{ij}.

Thus,

$$\begin{aligned} Q_1 &\equiv c_{11}P_1 + c_{12}P_2 + c_{13}P_3 \\ Q_2 &\equiv c_{21}P_1 + c_{22}P_2 + c_{23}P_3 \\ Q_3 &\equiv c_{31}P_1 + c_{32}P_2 + c_{33}P_3 \end{aligned} \tag{A.1}$$

If we denote the matrix of c_{ij} values C, then

$$P = CQ \tag{A.2}$$

To reverse the transformation, invert the matrix:

$$P \equiv C^{-1}Q \tag{A.3}$$

This same matrix can now be used to convert any set of values expressed in one set of primaries to the other set of primaries. Thus, the values p_1, p_2, and p_3 represent the amounts of the lights in primary system P needed to make a match.

$$\text{Sample} \equiv p_1 P_1 + p_2 P_2 + p_3 P_3 \tag{A.4}$$

Then we can calculate the values q in primary system Q simply by solving

$$q = Cp \tag{A.5}$$

APPENDIX B

CIE Color Measurement System

To determine a standard observer, a set of red, green, and blue lamps is used by a number of representative subjects to match all the pure colors of the spectrum. The result is called a set of *color-matching functions*. The set of color-matching functions for the Commission Internationale de l'Éclairage (CIE) standard observer is illustrated in Figure B.1. They were obtained with red, green, and blue pure spectral hues at 700, 546, and 436 nanometers, respectively, using a number of trained observers. Notice that there are negative values in these functions. These exist for the reasons discussed in Chapter 4. It is not possible to match directly all spectral lights with these, or any other, primaries.

For a number of reasons, the CIE chose not to use the standard-observer color-matching functions directly as the color standard, although it would have been perfectly legitimate to do so. Instead, they chose a set of abstract primaries called the *XYZ tristimulus values* and transformed the original color-matching functions into this new coordinate system. The process is the transformation from one coordinate system to another, as described in Appendix A. The transformed color-matching functions are illustrated in Figure B.2.

The CIE *XYZ* tristimulus values have the following properties:

1. All tristimulus values are positive for all colors. To achieve this, it was necessary to create primaries that do not correspond to any real lights. The *XYZ* primary axes are purely abstract concepts. However, this model has the advantage that all perceivable colors fall within the CIE gamut. They are, in effect, a set of virtual primaries.

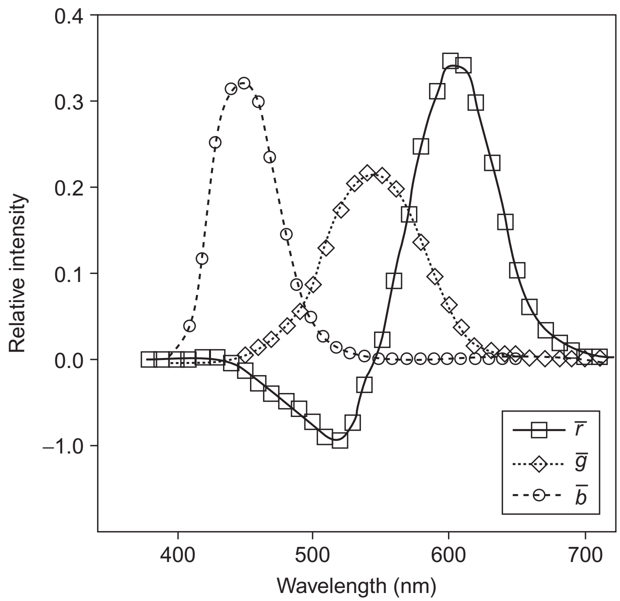

Figure B.1 The color-matching functions that define the CIE 1931 standard observer. To obtain these, each pure spectral wavelength was matched by a mixture of three primary lights.

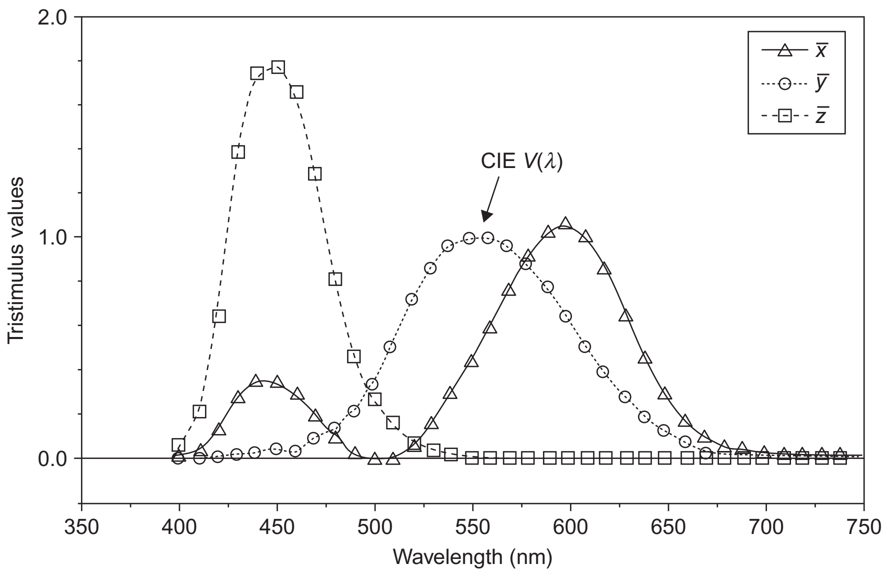

Figure B.2 The CIE tristimulus functions used to define the color of a light in *XYZ* tristimulus coordinates.

2. The X and Z tristimulus values have zero luminance. Only the Y tristimulus value contains luminance information, and the color-matching function ($\overline{y}$) is the same as the $V(\lambda)$ function, discussed in Chapter 3.

To determine the XYZ tristimulus values for a given patch of light, we integrate the energy distribution with the three $\overline{x}$, $\overline{y}$, $\overline{z}$ color-matching functions that define the CIE standard. Note that this is a generalization of the process of obtaining luminance described in Chapter 3—only here, we obtain three values to fully specify a color:

$$
\begin{aligned}
X &= K_m \int_{\lambda} E(\lambda)\overline{x}_{\lambda} d\lambda \\
Y &= K_m \int_{\lambda} E(\lambda)\overline{y}_{\lambda} d\lambda \\
Z &= K_m \int_{\lambda} E(\lambda)\overline{z}_{\lambda} d\lambda
\end{aligned}
\tag{B.1}
$$

If $K_m = 680$ lumens/watt and $E(\lambda)$ is measured in watts per unit area solid angle (steradians), then Y gives luminance.

This appendix provides only a very brief introduction to the complex and technical subject of colorimetry. Many important issues have been neglected that must be taken into account in serious color measurement. One issue is whether the light to be measured is an extended source, such as a monitor, in which case we measure in light emitted per unit area (candelas per square meter), or a lamp, in which case we measure total light output in all directions.

The subject becomes still more complex when we consider the measurement of surface colors; the color of the illuminating source must be taken into account, and we can no longer use a trichromatic system. Fortunately, computer monitors, because they emit light, do allow us to use a trichromatic system. The reader who intends to get involved in serious color measurement should obtain one of the standard textbooks, such as Wyszecki and Stiles (1982) or Judd and Wyszecki (1975).

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APPENDIX C

The Perceptual Evaluation of Visualization Techniques and Systems

There is a hierarchy of value in research. The ultimate goal of the scientist is to discover an immutable truth that will form the foundation for a new way of understanding the world. Applied researchers must often be satisfied with more humble objectives; sometimes it may be necessary to show that soon-to-be-obsolete interface *A* is better in some small way than soon-to-be-obsolete interface *B*. Between these two scenarios are many graduations. A research-based design guideline is something that can be of enduring value. A rough continuum of value exists, depending on the research goals. The following list starts with those goals that are most valuable.

Research Goals

Uncover fundamental truths and test theories. This is the holy grail of research—a fundamental truth that forever changes how we think of the world. Even small truths are to be prized. Because visualization techniques often produce patterns that do not exist in nature, or rarely do, studies of such techniques can be part of the new discipline of *information psychophysics*. Cognitive modeling of the way people interact with the interfaces to information systems is an important part of cognitive systems theory; and because all human intellectual achievements are ultimately the products of cognitive systems, not individuals alone, lasting truths may be achieved.

Discover the nature of the world. The early stages of science can be like butterfly collecting. It is necessary to get a feeling for the range of phenomena to be encompassed before developing theories. Some areas of perception are still like this. For example, the perception of patterns in motion is still at an early stage. The application of motion in visualization similarly lags.

Ascertain if an existing theory generalizes to practice. Many phenomena that are studied by vision researchers in the simplified conditions of the laboratory may not apply to a more complex data visualization. It can be a useful contribution simply to show that a well-known laboratory result generalizes to a common visualization problem.

Make an objective comparison between two or more display methods. Directly comparing two display methods can show which is the more effective. Ideally, the two methods should be tested with a variety of test data to provide some degree of generality.

Make an objective comparison between two or more display systems. Directly comparing two interfaces to an information system has obvious value to someone intending to choose one or the other. However, because system interfaces are typically complex, with usually dozens of differences between them, it is rarely possible to make valid generalizations from such studies.

Measure task performance. Simply measuring the time to perform a task with a particular interface is useful; it is even more useful if the task is elementary and frequently used. Error rates and error magnitudes are other common measurements providing useful guidelines for the designer of information systems.

Ascertain user preferences for different display methods. Occasionally, factors such as the "cool appearance" of a particular interface can be decisive in its adoption. Naturally, the techniques used for research should be suited to the goals of the research. Finding the balance between an attractive display and an optimal display for the task should be the goal.

This appendix is intended to provide a preliminary acquaintance with the kinds of empirical research methods that can be applied to visualization. It is not possible in a few thousand words to give a complete cookbook of experimental designs. When studies are looked at in detail, there are almost as many designs as there are research questions, but a number of broad classes stand out. It is generally the case that the methods used for evaluating visualization are borrowed from some other discipline, such as psychophysics or cognitive psychology. Such methods have been continually refined through the mill of peer review. For introductory texts on experimental design and data analysis, see Elmes et al. (1999) or Goodwin (2001). What follows is an introduction to some of the more common methodologies and measurement techniques.

Psychophysics

Psychophysics is a set of techniques based on applying the methods of physics to measurements of human sensation. These techniques have been extremely successful in defining the basic set of limits of the visual system. For example, how rapidly must a light flicker before it is perceived as steady, or what is the smallest relative brightness change that can be detected? Psychophysical techniques are ideal for discovering the important sensory dimensions of color, visual texture, sound, and so on, and more than a century of work already exists. Psychophysicists insist on a precise physical definition of the stimulus pattern. Light levels, temporal characteristics, and spatial characteristics must all be measured and controlled.

Psychophysical techniques are normally used for studies intended to reveal early sensory processes, and it is usually assumed (sometimes wrongly) that instructional biases are not significant in these experiments. Extensive studies are often carried out using only one or two observers, frequently the principal investigator and a lab assistant or student. These results are then generalized to the entire human race, with a presumption that can infuriate social scientists. Nevertheless, for the most part, scientific results—even those obtained with few subjects or as early as the 19th century—have withstood the test of time and dozens of replications. Indeed, because some of the experiments require hundreds of hours of careful observation, experiments with large subject populations are usually out of the question.

If a measured effect is easily altered because of instructional bias, we must question whether psychophysical methods are appropriate. The sensitivity of a measurement to how instructions are given can be used as a method for teasing out what is sensory and what is arbitrary. If a psychophysical measurement is highly sensitive to changes in the instructions given to the subject, it is likely to be measuring something that has higher-level cognitive or cultural involvement.

A few of the studies that have been published in recent years can be understood as a new variant on psychophysics, namely *information psychophysics*. The essence of information psychophysics is to apply methods of classical psychophysics to common information structures, such as elementary flow patterns, surface shapes, or paths in graphs.

When designing studies in information psychophysics, it is important to use meaningful units. For specifying the size of graphical objects there are three possibilities: pixels, centimeters, and visual angle. Each of these can be important. For larger objects, the size in centimeters and the visual angle should be determined. For small objects, pixel size can also be an important variable, and this should be specified. If you want to get really serious about color, then the monitor should be calibrated in some standard way, such as the CIE *XYZ* standard (Wyszecki, 1982). For moving objects, it is also important to know both the refresh rate (the frame rate of the monitor) and how fast your computer graphics are actually changing (update rate). It is worth thinking about how a graphics system actually works to get a better idea of the true precision of measurement. For example, if the update rate and refresh rate of the display are 60 Hz, then the granularity of measurement cannot be better than 16 msec.

Following are some of the common psychophysical methods that may also be applied to information psychophysics.

Detection Methods

There is a range of techniques that rely on how many errors people make when performing a certain task. Sometimes, determining an *error rate* is the goal of the experiment. If, for example, a visualization is used as part of an aircraft inspection process, then the expected error rate of the inspector is a critical issue.

More commonly, error rates are used as a rigorous way of finding thresholds. The idea is to keep showing subjects a display with some parameter at a range of levels. The percentage of correct detections is measured at each level, and a plot like Figure C.1 is generated. We define the threshold by some error rate; for example, if the chance error rate is 50%, then we might define the threshold as 75%. A problem with this process is that it requires a large number of trials to get a percent error rate for each level of our test parameter, and this can be especially difficult if the region of the threshold is not known. Hundreds of trials can be wasted making measurements that are well above, or below, the threshold.

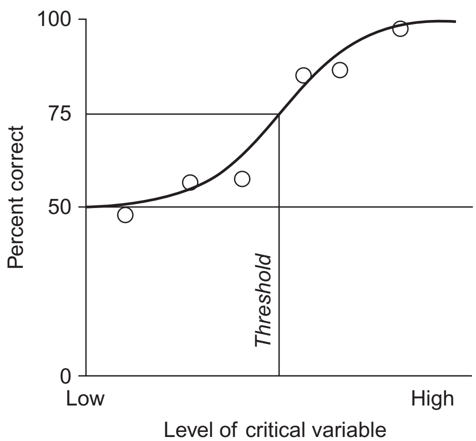

Figure C.1 The threshold in this particular example is defined as a 75% correct rate of responding. Errors are determined at many levels of a critical variable. A curve is fit through the points (heavy line) and this is used to define the threshold.

The *staircase procedure* is a technique for speeding up the determination of thresholds using error rates. The subject's responses are used to home in on the region of the threshold. If the subject makes a correct response to a target, the stimulus level is lowered for the next trial. If a subject fails to see a target, the stimulus level is raised. In this way, the program homes in on the threshold (Wetherill & Levitt, 1965).

The most sophisticated way of using error rates in determining thresholds for pattern detection is based on *signal detection theory*. A target pattern is assumed to produce a neural signal with a normal distribution, in the presence of neural noise caused by other factors. A parameter in the model determines whether observers are biased toward positive responses (producing false positives) or negative responses (producing false negatives). One way to represent the results of a study using signal detection theory is the *receiver operating characteristics* (ROC) *curve* (Swets, 1996; Irwin & McCarthy, 1998).

Method of Adjustment

A useful technique for tuning up a visualization is to give application domain experts control over some variable and ask them to adjust it so that it is optimal in some way for them. This is called the *method of adjustment*. Get a population of users to do this, and a useful default setting can be derived from the mean or median setting.

The method of adjustment can also be used to answer questions about perceptual distortion. For example, if we are interested in simultaneous lightness contrast, we can ask subjects to adjust a patch of gray until it matches some other gray and use the difference to estimate the magnitude of the distortion due to contrast.

There are biases associated with method of adjustment. If we are interested in the threshold for just seeing a target, we might turn up the contrast until it is visible or turn down the contrast until it disappears. The threshold will be lower in the latter case. Once we can see something, it is easier to perceive at a lower contrast.

Cognitive Psychology

In cognitive psychology, the brain is treated as a set of interlinked processing modules. A classic example of a cognitive model is the separation of short-term and long-term memory. Short-term memory, also called *working memory*, is the temporary buffer where we hold concepts, recent percepts, and plans for action. Long-term memory is a more or less permanent store of information that we have accumulated over a lifetime.

Methods in cognitive psychology commonly involve *measuring reaction time* or *measuring errors*, always with the goal of testing a hypothesis about a cognitive model. Typical experiments involve very simple, but ideally important tasks, such as determining whether or not a particular object is present in a display. The subject is asked to respond by hitting a key as fast as possible. The resulting time measurement can be used to estimate the time to perform simple cognitive operations, once the time taken to physically move the hand or depress a key is subtracted.

Another common kind of experiment measures *interference* between visual patterns. The increase in errors that results is used as evidence that different channels of information processing converge at some point. For example, if the task of mentally counting down in sevens from 100 were to interfere with short-term memory for the locations of objects in space, it would be taken as evidence that these skills share some common cognitive processing. The fact that there is little or no interference suggests that visual short-term memory and verbal short-term memory are separate (Postma & De Haan, 1996).

Recently, some cognitive theories have gained a tremendous boost because of advances in brain imaging. Functional MRI techniques have been developed that allow researchers actually to see which parts of the brain are active when subjects perform certain tasks. In this way, functional units that had only been previously inferred have actually been pinpointed (Zeki, 1993).

Structural Analysis

In structural analysis, theories of cognitive processing are constructed using direct observation as evidence. Structuralist researchers conduct studies that are more like interviews than formal experiments. Often the subjects are required to carry out certain simple tasks and report at the same time on their understanding and their perceptions. Using these techniques, researchers such as Piaget have been able to open up large areas of knowledge very rapidly and to establish the basic framework of our scientific understanding. However, in some cases, the insights obtained have not been confirmed by subsequent, more careful experiments. In structuralism, emphasis is given to hypothesis formation, which at times may seem more like the description and classification of behavior than a true explanation.

A structural analysis is often especially appropriate to the study of computer interfaces, because it is fast-moving and can take a variety of factors into account. We can quantify judgments to some extent through the use of rating scales. By asking observers to assign numbers to subjective effectiveness, clarity, and so on, we can obtain useful numerical data that compares one representation to another. There are several tools of structural analysis. We can ask domain experts what they need in a visualization *(requirements analysis)*. We can try to understand what they are attempting to accomplish at a more elementary level *(task analysis)*. Research tools also include testbench applications, *semistructured interviews*, and rating scales.

Testbench Applications for Discovery

At the early, butterfly-collecting stage of science, the goal is to map out the range of phenomena that exist. In visualization research, the goal is to gain an intuitive understanding of diversity, notable phenomena, and what works and does not work from an applied perspective.

The primary early-stage tool for the visualization researcher is the *testbench application*. It gives the researcher the flexibly to try out different ways of mapping the data into a visual representation. Of course, there is no such thing as a universal testbench. The goal should be to build a flexible tool capable of producing a range of visual mappings of the data and a range of interaction possibilities. For example, if the problem is to find the best way to represent the shape of a surface, the testbench application should be able to load different surface shapes, change lighting, change surface texture properties, turn stereoscopic viewing on and off, and provide motion parallax cues.

There is a tendency for programmers to make the user interface for a testbench too sophisticated. This can be self-defeating, because it limits flexibility. The objective should be to explore, not to build a polished application for scientists. If the easiest way to explore is to change a constant in the code and recompile, then this is what should be done. Often a good testbench interface is a text file of parameters, setting various aspects of the display. This can be modified in a word processor and reloaded. Sometimes a panel of sliders is useful, allowing a researcher to adjust parameters interactively. For the most part, the quality of the code does not matter for a testbench application, although it is essential that the parts of the program dealing with display parameters are correct.

There are many ways to play with testbenches, and *play* is definitely the operative word. This is a time for creative exploration, forming hypotheses quickly and discarding them easily. Interesting possibilities can be shown to domain experts. It is especially useful to show them the best solutions you have. You may only get one chance to have a physicist, an oceanographer, or a surgeon to take you seriously. Asking their opinions about something that actually looks better than whatever they are currently using is one way to get their interest. Phenomena that may be significant can be shown to other vision researchers.

Once something interesting has been identified with a testbench, a rigorous study can be carried out using the methods of psychophysics or cognitive psychology.

Structured Interviews

One of the most useful tools, both for initial requirements and task analysis and for the evaluation of problem solutions, is the *structured* or *semistructured* interview. The method is to construct an interview with a structured set of questions to elicit information about specific task requirements. It is structured to make sure that the important questions are asked and that the answers come in a somewhat coherent form.

Structured interviews can be excellent tools to evaluate what aspects of a visualization actually are important to potential users. They can also be used to evaluate a number of different solutions for strengths and weaknesses. In many cases, it is useful for structured interviews to be built around the performance of particular tasks. The participant is asked to perform particular tasks with the system or with more than one system and is then asked to comment on suitability, ease of use, clarity of presentation, and so on. The great advantage of structured interviews is that they make it possible to gain information about a wide range of issues with relatively little effort, in comparison with more objective methods, such as reaction time or error rate measurements. Also, you might learn something you did not ask about.

Rating Scales

The Likert scale (also called a *rating scale*) is a method for turning opinions into numbers. Subjects are simply asked to rate some phenomenon by choosing a number on some range, such as the following:

(GOOD) 1 2 3 4 5 (BAD)

For example, if we have six different visual representations of a flow pattern, we might ask subjects to rate how well they can see each pattern on a scale of 1 to 5.

Subjects tend to use rating scales in their own idiosyncratic ways. Some will be biased to the low end of the scale and others to the upper end, but generally they will tend to try to use most of the scale for whatever set of samples they are shown. Because of this, no absolute meaning should ever be given to rating scale data. If 10 inferior visual representations are shown to subjects, they will still differentiate them into good and bad; the same will be true for 10 very good ones. However, rating scales are an excellent tool for measuring relative preferences.

Rating scales can be used to answer broad questions about preferences for two or more different solutions to a problem. Quite often, users will prefer one solution to another, even though no objective differences are measured. In some cases, one interface might even be objectively superior, but another preferred.

Statistical Exploration

Sometimes it may be useful to use statistical discovery techniques to learn about some class of visualization methods. Suppose we wish to carry out an investigation into how many data dimensions can be conveyed by visual texture. The first obvious question is: How many perceptually distinct texture dimensions are there? The next question is: How can we effectively map data dimensions to them? If the answer cannot be found in the research literature, one way to proceed is to use a kind of statistical data-mining strategy to find the answer. First, we might ask people to classify textures in as many different ways as we can think of (e.g., roughness, regularity, elongation, fuzziness). The next step is to apply a statistical method to discover how many dimensions there really are in the subjects' responses. The following sections list the major techniques.

Principal Components Analysis

The goal of *principal components analysis* is to take a set of variables and find a new set of variables (the principal components) that are uncorrelated with each other (Young, Takane, & de Leeuw, 1978; Tabachnick & Fidell, 2001; Hotelling, 1933). This might be used to reduce a high-dimensional data set to lower dimensions. In many data sets (think of multiple measurements on the dimensions of parts of beetles, for example), many of the variables are highly correlated, and the first two or three principal components contain most of the variability in the data. If this is the case, then one immediate advantage of the data reduction resulting from PCA is that the data can be mapped into a two- or three-dimensional space and thereby visualized as a scatterplot.

Multidimensional Scaling

Multidimensional scaling (MDS) is a method explicitly designed to reduce the dimensionality of a set of data points to two or three, so that these dimensions can be displayed visually. The method is designed to preserve, as far as possible, metric distances between data points (Young et al., 1978; Wong & Bergeron, 1997).

Clustering

Cluster analysis is a statistical technique designed to find clusters of points in a data space of any dimensionality (Romesburg, 1984). There are two basic kinds: hierarchical and k-means. In *hierarchical clustering*, a tree structure is built, with individual data points at the leaves. These points are combined recursively, with the most similar first. Hierarchical clustering can provide the basis for hierarchical taxonomy.

K-means clustering requires the user to input a number of clusters (k). A set of k clusters is generated by finding the cluster means that minimize the sum of squared distances between each set of data points and its nearest mean.

Either kind of clustering can be used as a method for data reduction in visualization, because a tight cluster of points can be reduced to a single data glyph.

Multiple Regression

In visualization, *multiple regression* is a statistical technique that can be used to discover whether it is possible to predict some response variable from display properties. For example, the time required to judge the shortest path in a node–link diagram might be predicted from the number of link crossings in the diagram and the bendiness of the path (Ware, Purchase, Colpoys, & McGill, 2002).

Cross-Cultural Studies

If sensory codes are indeed interpreted easily by all humans, this proposition should be testable by means of *cross-cultural studies*. In a famous study by Berlin and Kay (1969), color naming was compared across more than 100 languages. In this way, the researchers established the universality of certain color terms, equivalent to our red, green, yellow, and blue. This study is supported by neurophysiological and psychophysical evidence that suggests these basic colors are hardwired into the human brain. Such studies are rare, for obvious reasons, and with the globalization of world culture, meaningful studies of this type are rapidly becoming impossible. Television is bringing about an explosive growth in universal symbols. In the near future, cross-cultural studies aimed at basic questions relating to innate mechanisms in perception may be impossible.

Child Studies

By using the techniques of *behaviorism*, it is possible to discover things about a child's sensory processing even before the child is capable of speech. Presumably, very young children have only minimal exposure to the graphic conventions used in visualization. Thus, the way they respond to simple patterns can reveal basic processing mechanisms. This, of course, is the basis for the Hochberg and Brooks (1978) study discussed in Chapter 1.

It is also possible to gain useful data from somewhat older children, such as five-year-olds. They presumably have all the basics of sensory processing in place, but they still have a long way to go in learning the graphic conventions of our culture, particularly in those obscure areas that deal with data visualization.

Practical Problems in Conducting User Studies

Experimenter Bias

Researchers' careers depend on what they publish, and it is much easier to publish results that confirm a hypothesis than results showing no effects. There are many opportunities for experimenter bias in both the gathering and the interpretation of results.

As a rule of thumb, if the data being measured relates to some low-level, fundamental aspect of vision, then it will be less subject to bias. For example, if a subject is given a control that allows the setting of what seems to be a "pure" yellow, neither reddish nor greenish, the setting is likely to be extremely consistent and will be relatively robust even if the experimenter makes comments like "Are you sure that's not a little tinged with green?" On the other hand, if the experimenter says, "I want you to rate this system, developed by me to obtain my PhD, in comparison with this other system, developed at the University of Blob," then experimenter bias effects can be extreme.

When considering your own work or that of others, be critical. The great advantage of science is that it is incremental and always open to reasoned criticism. Applied science tends to adopt somewhat looser standards, and replications of experiments are rare. Many of the studies we read are biased. In evaluating a published result, always look to see whether the data actually supports what is being claimed. It is common for claims to be made that go far beyond the results. Often the abstract and title suggest that some method or other has clearly been demonstrated to be superior. An examination of the method may show otherwise. A common example is when a difference that is not statistically significant is claimed to support a hypothesis. Some of the most important questions to ask are:

What is the task?

Does the experiment really address the intended problem?

Are the control conditions appropriate?

Does the experiment actually test the stated hypothesis?

Are the results significant?

Are there possible confounding variables?

Confounding variables are variables that change in the different experimental conditions, although they are not the variables that the researchers claim to be responsible for the measured effect.

How Many Subjects to Use?

In vision research, some kinds of studies are run with only two, three, or four subjects. These are studies that purport to be looking at the low-level machinery of vision. It makes sense; humans all have the same visual system, and to measure its properties you do not need a large sample of the population. On the other hand, if you are interested in how color terms are used in the general population, then the general population must be sampled in some way.

Statistically, the number of subjects and the number of observations required depend on the variability of responses with a single subject and the variability from one subject to another.

Most experiments are run with between 12 and 20 subjects, where all of the experimental conditions can be carried out on the same subjects (a *within subjects* design). In some cases, because of learning effects, different subjects must be assigned to different conditions. Such experiments will require more subjects.

Research is always an optimization problem—how to get the most information with the least effort. One reason there have been so many simple reaching experiments presented at the Association for Computing Machinery (ACM) Computer-Human Interaction (CHI) conferences is that a Fitts' law experiment (the standard experimental method) is very easy to carry out; it is possible to gather a data point every two or three seconds. A substantial amount of data can be gathered in half an hour of subject time, making it possible to run large numbers of subjects.

Combinatorial Explosion

One of the major problems in designing a visualization study is deciding on the *independent variables*. Independent variables are set by the experimenter in the design stage. In a study of the effectiveness of flow visualization, independent variables might be line width and line spacing of streamlines. The *dependent variables* are the measured user responses, such as the amount of error in judging the flow direction.

In visualization design problems, there are often many possible independent variables. Let us take the example of flow visualization consisting of streaklets—small, curved line segments showing the direction of flow. Streaklet length, streaklet start width, streaklet end width, streaklet start color, streaklet end color, and background color may all be important. Suppose we would like to have four levels of each variable and we wish to study all possible combinations. The result is $4^6 = 2048$ different conditions. Normally, we would like at least 10 measurements of user performance in each condition. We will require over 20,000 measurements. If it were to take 30 seconds to make each measurement, the result would be more than 160 hours of observation for each subject. We might decide to have 15 subjects in our experiment. This means over a year of work, running subjects 40 hours per week. For most researchers, such a study would be impossibly large.

The brute force approach to experimental design is to include all variables of interest at all meaningful levels. Because of the combinatorial explosion that results, this cannot work. The way to obtain more from studies, with less effort, is to develop either theories or descriptive models that can be applied to a range of design problems. Empirical studies can be much simpler and focus on specific aspects of the theory.

Task Identification

A critical element in experimental design is deciding on the *task* the subject is to perform. Ideally, this will be something that is both theoretically interesting and very commonly used in real applications. Even if the exact task is not common, it should be representative of activities that are common in visualization interfaces. For example, if the application domain involves visualizing node–link diagrams, the subject might be asked if there is a path between two highlighted nodes. This task is good, because perceiving links between nodes is likely to be important for almost all of the great variety of node–link diagrams that exist.

In order to provide a useful measure of performance, it is also important that the task can be set up to have a clear and simple user response. For example, the subject might push the right mouse button to indicate *yes* and the left mouse button to indicate *no*.

Controls

In an experimental design, a *control* is a condition that is used to provide some basis for comparison. In a theoretical study, the control is usually some condition that provides a reference for theory testing. A theory might predict that a contrast effect will bias a judgment by 30%; the control measurement would be made without the contrast-causing factor to provide a baseline for comparison.

In evaluating a new visualization method, the most reasonable control is the current best practice display method. Some studies employ the somewhat dishonest practice of using a very poor alternative method as a control, thereby exaggerating the value of their own method. This is one of the reasons that the research literature should be read with a measure of skepticism.

Getting Help

Studies in information visualization are fundamentally multidisciplinary. Usually knowledge of computer science, human visual perception, and some application domain is necessary. Often, the best way to do research is to be part of a collaborative team—a computer scientist who can design and build novel interactive visualization systems, a psychologist who understands the perceptual issues and has experience in perception and cognition research, and a domain expert who understands the potential application. Naturally, everyone has his or her own area of interest, and finding compatible collaborators can be difficult, but it can also be very rewarding.

In reality, a single researcher must take on several roles, although getting help and advice is usually worth the effort. Most academics are willing to provide a certain amount of free advice for no more reward than a line in the acknowledgments section of a published paper.

Finally, many universities operate a statistical consulting service that can provide help in experimental design or data analysis.

APPENDIX D

Guidelines

Chapter 1

	Page number
[G1.1] Design graphic representations of data by taking into account human sensory capabilities in such a way that important data elements and data patterns can be quickly perceived.	14
[G1.2] Important data should be represented by graphical elements that are more visually distinct than those representing less important information.	14
[G1.3] Greater numerical quantities should be represented by more distinct graphical elements.	14
[G1.4] Graphical symbol systems should be standardized within and across applications.	17
[G1.5] Where two or more tools can perform the same task, choose the one that allows for the most valuable work to be done per unit time.	24
[G1.6] Consider adopting novel design solutions only when the estimated payoff is substantially greater than the cost of learning to use them.	24
[G1.7] Unless the benefit of novelty outweighs the cost of inconsistency, adopt tools that are consistent with other commonly used tools.	24
[G1.8] Effort spent on developing tools should be in proportion to the profits they are expected to generate. This means that small-market custom solutions should be developed only for high-value cognitive work.	25

Chapter 2

	Page number
[G2.1] Use Lambertian shading to reveal the shapes of smooth surfaces.	40
[G2.2] Use specular shading to reveal fine surface details. Make it possible to move the light source or rotate the object so that specular light is reflected from regions of critical interest.	40
[G2.3] Consider using cast shadows to reveal large-scale spatial relationships. Shadows should be created only where the connection between the shadow and the casting object is clear and where the value of the additional information outweighs the information that it obscured.	40
[G2.4] Consider applying ambient occlusion in the lighting model to support two-dimensional (2D) shape perception for objects that otherwise supply no shading information.	41
[G2.5] In augmented-reality systems, an augmenting image linked to an external object should be at the same focal distance.	46
[G2.6] In augumented-reality systems, when augmenting imagery does not need to be linked to external objects, the focal distance of the augumenting imagery should be closer, which will reduce visual interference. This will not work for older users who have little or no ability to change the focus of their eyes.	46
[G2.7] When using a head-mounted display to read text, make the width of the text area no more that 18 degrees of visual angle.	47
[G2.8] Use a high-resolution display with a moderate viewing angle (e.g., 40 degrees) for data analysis. This applies both to individual data analysis when the screen can be on a desktop and close to the user and to collaborative data analysis when the screen must be larger and farther away.	58
[G2.9] Use wrap-around screens to obtain a sensation of "presence" in a virtual space. This is useful in vehicle simulations and some entertainment systems.	58
[G2.10] Avoid using high-contrast grating patterns in visual displays. In particular, avoid using high-contrast grating patterns that flicker or any pattern flickering at rates between 5 Hz and 50 Hz.	62
[G2.11] Antialias visualizations wherever possible, especially where regular patterns, fine textures, or narrow lines are being displayed.	66

Chapter 3

	Page number
[G3.1] Avoid using gray scale as a method for representing more than a few (two to four) numerical values.	75
[G3.2] Consider using Cornsweet contours instead of simple lines to define convoluted bounded regions.	77

[G3.3] Consider using adjustments in luminance contrast as a highlighting method. It can be applied by reducing the contrast of unimportant items or by locally adjusting the background to increase the luminance contrast of critical areas.	79
[G3.4] Use a minimum 3:1 luminance contrast ratio between a pattern and its background whenever information is represented using fine detail, such as texture variation, small-scale patterns, or text.	82
[G3.5] If subtle gray-level gradations within the bounds of a small object are important, create low-luminance contrast between the object and its background.	89
[G3.6] Ideally, when setting up a monitor for viewing data, a light neutral-colored wall behind the screen should reflect an amount of light comparable to the level of light coming from the monitor. The wall facing the screen should be of low reflectance (mid- to dark gray) to reduce reflections from the monitor screen. Lights should be placed so that they do not reflect from the monitor screen.	91
[G3.7] When setting up a room for a projection system, ensure that minimal room light falls on the projector screen. This can be done by means of baffles to shield the screen from direct illumination. Low-reflectance (mid- to dark gray) walls are also desirable, as the walls will scatter light, some of which inevitably reaches the screen.	91

Chapter 4

	Page number
[G4.1] Use more saturated colors when color coding small symbols, thin lines, or other small areas. Use less saturated colors for coding large areas.	108
[G4.2] When small symbols, text, or other detailed graphical representations of information are displayed using color on a differently colored background, always ensure luminance contrast with the background. This guideline is a variation of G3.4.	112
[G4.3] Ensure adequate luminance contrast in order to define features important for perceiving stereoscopic depth.	112
[G4.4] Ensure adequate luminance contrast in order to define features important for perceiving moving targets.	112
[G4.5] When applying shading to define the shape of a curved surface, use adequate luminance (as opposed to chromatic) variation. This is a supplement to G2.1.	113
[G4.6] If large areas are defined using nearly equiluminous colors, consider using thin border lines with large luminance differences (from the colors of the areas) to help define the shapes.	113
[G4.7] If using color saturation to encode numerical quantity, use greater saturation to represent greater numerical quantities. Avoid using a saturation sequence to encode more than three values.	117
[G4.8] In an interface for specifying colors, consider laying out the red–green and yellow–blue channel information on a plane. Use a separate control for specifying the dark–light dimension.	119

[G4.9] In an interface for designing visualization color schemes, consider providing a method for showing colors against different backgrounds.	120
[G4.10] To support the use of easy-to-remember and consistent color codes, consider providing color palettes for designers.	122
[G4.11] Consider using red, green, yellow, and blue to color code small symbols.	123
[G4.12] For small color-coded symbols, ensure luminance contrast with the background as well as a large chromatic differences with the background.	123
[G4.13] If colored symbols may be nearly isoluminant against parts of the background, add a border having a highly contrasting luminance value to the color, for example, black around a yellow symbol or white around a dark blue symbol.	124
[G4.14] To create a set of symbol colors that can be distinguished by most color-blind individuals, ensure variation in the yellow–blue direction.	124
[G4.15] Do not use more than ten colors for coding symbols if reliable identification is required, especially if the symbols are to be used against a variety of backgrounds.	124
[G4.16] Use low-saturation colors to color code large areas. Generally, light colors will be best because there is more room in color space in the high-lightness region than in the low-lightness region.	125
[G4.17] When color coding large background areas overlaid with small colored symbols, consider using all low-saturation, high-value (pastel) colors for the background, together with high-saturation symbols on the foreground.	125
[G4.18] When highlighting text by changing the color of the font, it is important to maintain luminance contrast with the background. With a white background, high-saturation dark colors must be used to change the font color. Alternatively, when changing the background color, low-saturation light colors should be used if the text is black on white.	126
[G4.19] Use a spectrum approximation pseudocolor sequence for applications where its use is deeply embedded in the culture of users. This kind of color sequence can also be used where the most important requirement is reading map values using a key. If this sequence is used, the spacing of the colors should be carefully chosen to provide discriminable steps.	130
[G4.20] If it is important to see highs, lows, and other patterns at a glance, use a pseudocolor sequence that monotonically increases or decreases in luminance. If reading values from a key is also important, cycle through a variety of hues while trending upward or downward in luminance.	131

Chapter 5

	Page number
[G5.1] To minimize the cost of visual searches, make visualization displays as compact as possible, compatible with visual clarity. For efficiency, information nodes should be arranged so that the average saccade is 5 degrees or less.	141

[G5.2] Use different visual channels to display aspects of data so that they are visually distinct.	145
[G5.3] To make symbols easy to find, make them distinct from their background and from other symbols; for example, the primary spatial frequency of a symbol should be different from the spatial frequency of the background texture and from other symbols.	149
[G5.4] Make symbols as distinct from each other as possible, in terms of both their spatial frequency components and their orientations components.	151
[G5.5] Make symbols as distinct as possible from background patterns in terms of both their spatial frequency components and their orientation components.	151
[G5.6] Use strong preattentive cues before weak ones where ease of search is critical.	156
[G5.7] For maximum popout, a symbol should be the only object in a display that is distinctive on a particular feature channel; for example, it might be the only item that is colored in a display where everything else is black and white.	157
[G5.8] Use positively asymmetric preattentive cues for highlighting.	158
[G5.9] For highlighting, use whatever feature dimension is used least in other parts of the design.	158
[G5.10] When color and shape channels are already fully utilized, consider using motion or blink highlighting. Make the motion or blinking as subtle as possible, consistent with rapid visual search.	158
[G5.11] To make symbols in a set maximally distinctive, use redundant coding wherever possible; for example, make symbols differ in both shape and color.	159
[G5.12] If symbols are to be preattentively distinct, avoid coding that uses conjunctions of basic graphical properties.	160
[G5.13] When it is important to highlight two distinct attributes of a set of entities, consider coding one using motion or spacial grouping and the other using a property such as color or shape.	161
[G5.14] If it is important for people to respond holistically to a combination of two variables in a set of glyphs, map the variables to integral glyph properties.	165
[G5.15] If it is important for people to respond analytically to a combination of variables, making separate judgments on the basis of one variable or the other, map the variables to integral glyph properties.	165
[G5.16] When designing a set of glyphs to represent quantity, mapping to any of the following glyph attributes will be effective: size, lightness (on a dark background), darkness (on a light background), vividness (higher saturation) of color, or vertical position in the display.	168
[G5.17] Ideally, use glyph length or height, or vertical position, to represent quantity. If the range of values is large, consider using glyph area as an alternative. Never use the volume of a three-dimensional glyph to represent quantity.	169
[G5.18] In general, the use of heterogeneous display channels is best combined with meaningful mappings between data attributes and graphical features of a set of glyphs.	172
[G5.19] When designing user interrupts, peripheral alerting cues must be made stronger if the cognitive load is expected to be high.	174

Chapter 6

	Page number
[G6.1] Place symbols and glyphs representing related information close together.	181
[G6.2] When designing a grid layout of a data set, consider coding rows and/or columns using low-level visual channel properties, such as color and texture.	182
[G6.3] To show relationships between entities, consider linking graphical representations of data objects using lines or ribbons of color.	183
[G6.4] Consider using symmetry to make pattern comparisons easier, but be sure that the patterns to be compared are small in terms of visual angle (<1 degree horizontally and <2 degrees vertically). Symmetrical relations should be arranged on horizontal or vertical axes unless some framing pattern is used.	185
[G6.5] Consider putting related information inside a closed contour. A line is adequate for regions having a simple shape. Color or texture can be used to define regions that have more complex shapes.	187
[G6.6] To define multiple overlapping regions, consider using a combination of line contour, color, texture, and Cornsweet contours.	188
[G6.7] Use a combination of closure, common region, and layout to ensure that data entities are represented by graphical patterns that will be perceived as figures, not ground.	190
[G6.8] For vector field visualizations, use contours tangential to streamlines to reveal the orientation component.	198
[G6.9] To represent flow direction in a vector field visualization, use streamlets with heads that are more distinct than tails, based on luminance contrast. A *streamlet* is a glyph that is elongated along a streamline and which induces a strong response in neurons sensitive to orientations tangential to the flow.	198
[G6.10] For vector field visualizations, use more distinct graphical elements to show greater field strength or speed. They can be wider, longer, more contrasting, or faster moving.	199
[G6.11] Consider using texture to represent continuous map variables. This is likely to be most effective where the data varies smoothly and where surface shape features are substantially larger than texture element spacing.	202
[G6.12] In order to make a set of nominal coding textures distinctive, make them differ as much as possible in terms of dominant spatial frequency and orientation components. As a secondary factor, make texture elements vary in the randomness of their spacing.	205
[G6.13] Use simple texture parameters, such as element size or element density, only when fewer than five ordinal steps must be reliably distinguished.	206
[G6.14] To display a bivariate scalar field, consider mapping one variable to color and a second variable to variations in texture.	209

[G6.15] To design textures so that quantitative values can be reliably judged, use a sequence of textures that are both visually ordered (for example, by element size or density) and designed so that each member of the sequence is distinct from the previous one in some low-level property. 209

[G6.16] When using overlapping textures to separate overlapping regions in a display, avoid patterns that can lead to aliasing problems when they are combined. 212

[G6.17] When using textures in combination with background colors for overlapping regions, choose lacy textures so that other data can be perceived through the gaps. 212

[G6.18] When using lacy textures in combination with colors for overlapping regions, ensure luminance contrast between texture elements in the foreground and color-coded data presented in the background. 213

[G6.19] To display discrete data with more than four dimensions, consider using color-enhanced generalized draftsman's plots in combination with brushing. 218

[G6.20] Make every effort to standardize the mapping of data to visual patterns within and across applications. 220

[G6.21] In search tasks for infrequent targets, insert retraining sessions during which targets are frequent and feedback is given regarding success or failure. 221

[G6.22] When developing glyphs, use small, closed shapes to represent data entities, and use the color, shape, and size of those shapes to represent attributes of those entities. 224

[G6.23] Use connecting lines, enclosure, grouping, and attachment to represent relationships between entities. The shape, color, and thickness of lines and enclosures can represent the types of relationships. 226

[G6.24] As an alternative to arrows to represent directed relationships in diagrams, consider using tapered lines with the broadest end at the source node. 226

[G6.25] Use closed contours, areas of texture, or areas of color to denote geographic regions. Use color, texture, or boundary style to denote the type of region. 228

[G6.26] Use lines to represent paths and linear geographic features. Use line color and style to represent the type of linear feature. 228

[G6.27] Use small, closed shapes to represent point entities, such as cities, that appear small on a map. Use color, shape, and size to represent attributes of these entities. 228

[G6.28] Consider using a treemap to display tree structured data where it is only necessary to display the leaf nodes and where it is important to display a quantity associated with each leaf node. 229

[G6.29] Consider using a node–link representation of a tree where the hierarchical structure is important, where internal (non-leaf) nodes are important, and where quantitative attributes of nodes are less important. 229

[G6.30] When animation is used in a visualization, aim for motion in the range of 0.5 to 4 degrees/second of visual angle. 232

Chapter 7

	Page number
[G7.1] If accurate size judgments are required for abstract 3D shapes viewed in a computer-generated 3D scene, provide the best possible set of depth cues.	242
[G7.2] To minimize perceived distortions from off-axis viewing of 3D data spaces, avoid extremely wide viewing angles when defining perspective views. As a rule of thumb, keep the horizontal viewing angle below 30 degrees.	245
[G7.3] In 3D visualizations of height field data, consider using draped grids to enhance surface shape information. This is likely to be most useful where the data varies smoothly so surface shape features are substantially larger than grid squares.	253
[G7.4] In 3D data visualizations, consider using cast shadows to tie objects to a surface that defines depth. The surface should provide strong depth cues, such as a grid texture. Only use cast shadows to aid in depth perception where the surface is simple and where the objects casting the shadow are close to it.	255
[G7.5] To help users understand depth relationships in 3D data visualizations, consider using structure-from-motion by rotating the scene around the center of interest. This is especially useful when objects are unattached to other parts of the scene.	258
[G7.6] When creating stereoscopic images, avoid placing graphical objects so that they appear in front of the screen and are clipped by the edges of the screen. The simplest way of doing this is to ensure that no objects are in front of the screen in terms of their stereoscopic depth.	261
[G7.7] When creating stereoscopic displays for 3D visualizations, use the highest possible screen resolution, especially in a horizontal direction, and aim to achieve excellent spatial and temporal antialiasing.	262
[G7.8] When creating stereoscopic displays for 3D visualizations, adjust the virtual eye separation to optimize perceived stereoscopic depth while minimizing diplopia.	264
[G7.9] In 3D data visualizations where a strong, preferably gridded, ground plane is available, consider using drop lines to add depth information for small numbers of discrete isolated objects.	267
[G7.10] In 3D data visualizations, consider using halos to enhance occlusion where this is an important depth cue and where overlapping objects have the same color or minimal luminance difference.	267
[G7.11] In 3D data visualizations, understand and use the depth cues that are most important for the critical tasks in an application. Implement other cues on which these critical cues depend.	271
[G7.12] When it is critical to perceive large 3D node–link structures, consider using motion parallax, stereoscopic viewing, and halos.	275
[G7.13] Consider using textures to help reveal surface shapes, especially if they are to be viewed in stereo. This is only appropriate for relatively smooth surfaces and	280

where texture is not needed for some other attribute. Ideally, texturing should be low contrast so as not to interfere with shading information. Textures that have linear components are more likely to reveal surface shape than textures with randomly stippled patterns. When one 3D surface is viewed over another, the top surface should have lacey, see-through textures.

[G7.14] Consider using both structure-from-motion (by rotating the surface) and stereoscopic viewing to enhance the user's understanding of 3D shape in a 3D visualization. These cues will be especially useful when one textured transparent surface overlays another. 280

[G7.15] As a method for displaying bivariate scalar field maps, use a shaded height field for one variable and color coding for the other. This will work best if the shaded variable is relatively smooth. 282

[G7.16] To see depth in a 3D scatterplot, consider generating structure-from-motion cues by rotating or oscillating the point cloud around a vertical axes. Also use stereoscopic viewing if possible. 283

[G7.17] If it is important to judge the morphology of the outer boundary of a 3D cloud of points, consider employing a statistical approximation method to estimate the local orientation of the cloud surface and use this to shade the individual points. 283

[G7.18] To represent 3D trajectories, consider using shaded tube or box extrusions, with periodic bands to provide orientation cues. Also, apply motion parallax and stereoscopic viewing, if possible. 284

[G7.19] Use stereoscopic viewing when visually guided hand movements are critically important. If possible, use a graphical proxy for the user's hand and ensure accurate relative positioning between the hand proxy and the virtual objects to be manipulated. 287

[G7.20] In 3D environments that support one-to-one mapping between the user's hand and a virtual object, ensure that the relative positions of a hand proxy, such as a probe, and an object being reached for are correct. Also, minimize rotational mismatch (>30 degrees) between the virtual space and the actual space within which the user's hand is moving. 287

[G7.21] To define vertical polarity in a 3D data space, provide a clear reference ground plane and place recognizable objects on it that have a characteristic orientation with respect to gravity. 289

[G7.22] To create a vivid sense of presence in a 3D data space, provide a large field of view, smooth motion, and a lot of visual detail. 290

Chapter 8

Page number

[G8.1] For optimal identification, make important patterns and complex objects so that they have a size of approximately 4 to 6 degrees of visual angle. This is not a rigid requirement, as there is only a gradual fall-off in skill as we depart from the optimal. 295

[G8.2] Consider using an object display where standardized sets of data must be repeatedly analyzed and where the data can be mapped to semantically meaningful objects. 305

[G8.3] Design object displays in such a way that numbers are tied to recognizable visual objects representing system components. 305

[G8.4] Design object display layouts using connecting elements that clearly indicate the physical connections between components of a system. 305

[G8.5] Design object display glyphs to have emergent properties revealing the effect of important interactions between variables. 305

[G8.6] Design object display glyphs to become more salient when critical values are reached in the data. 305

[G8.7] Consider representing system components using geons—simple 3D shaded objects such as spheres, cylinders, cones, and boxes. 306

[G8.8] Consider using the color and surface texture of geons to represent secondary attributes of represented entities. 306

[G8.9] Consider using a geon-based diagram in instances where the diagram is relatively simple, fewer than 30 components, and where entities and relationships must be shown. 306

[G8.10] Consider representing relationships between components by means of joints between objects. Tubes can be used to express certain types of relations. A small geon attached to a larger geon can show that it is a component part. 307

[G8.11] Consider using geon shapes to represent the primary attribute of represented entities. 307

[G8.12] When creating 3D diagrams, lay out system components as much as possible in a 2D plane orthogonal to the line of sight. Be sure that connections between diagram components are clearly visible. 307

[G8.13] When creating 3D diagrams, consider placing an object inside a second transparent object to express a part-of relationship. 308

[G8.14] When creating diagrams showing entities and relationships, use properties such as size and thickness to represent the strength of the relationship between entities. 308

[G8.15] For perceptually efficient and compact expressions of human emotion, consider using small glyphs representing simplified faces. These are likely to be especially effective in conveying the basic emotions of anger, disgust, fear, happiness, sadness, and surprise. 309

[G8.16] To make a visual image that represents a class of things, use a canonical example in its normal orientation displayed from a typical viewpoint, but only if a suitable exemplar exists. 315

[G8.17] Consider using pictorial icons for pedagogical purposes in infographics. Use them only where a canonical or culturally defined image is available. 320

[G8.18] When a large number of data points must be represented in a visualization, use symbols instead of words or pictorial icons. 321

Chapter 9

Page number

Chapter 10

	Page number
[G10.1] For the fastest epistemic actions, use hover queries, activated whenever the mouse cursor passes over an object. These are only suitable where the query targets are dense and inadvertent queries will not be overly distracting.	349
[G10.2] When designing interfaces for two-handed data manipulations, the non-dominant hand (usually the left) should be used to control frame-of-reference information, while the dominant hand (usually the right) should be used to make detailed selections or manipulations of data.	350
[G10.3] When designing interfaces to move objects on the screen, be sure that object movement is in the same general direction as hand movement.	352
[G10.4] To support view navigation in 3D data spaces, a sufficient number of objects must be visible at any time to judge relative view position, and several objects must persist from one frame to the next to maintain continuity.	355
[G10.5] Consider providing an overview map to speed up the acquisition of a mental map of a data space.	360
[G10.6] Consider providing a small overview map to support navigation through a large data space.	360
[G10.7] When designing a set of landmarks, make each landmark visually distinct from the others.	361
[G10.8] When designing a landmark, make it recognizable as far as possible at all navigable scales.	361
[G10.9] In interfaces to view map data in 3D, the default controls should allow for tilt around a horizontal axis and rotation about a vertical axis, but not rotation around the line of sight.	363
[G10.10] When designing an overview map, provide a "you are here" indicator that shows location and orientation.	366
[G10.11] Maps used in navigation should provide three views: north-up, track-up, and track-up-perspective. A track-up perspective view should be the default.	366
[G10.12] When designing a visualization that uses geometric fisheye distortion methods, allow a maximum scale change factor of five.	368
[G10.13] Design fisheye distortion methods so that meaningful patterns are always recognizable.	370
[G10.14] When designing a zooming interface, set a default scaling rate of 3 to 4× (magnification or minification) per second. The rate should be user changeable so that experts can increase it.	371
[G10.15] For large 2D or 3D data spaces, consider providing one or more windows that show a magnified part of the larger data space. These can support a scale difference of up to 30 times. In the overview, provide a visual proxy for the locations and directions of the magnified views.	373

Chapter 11

	Page number
[G11.1] Design cognitive systems to maximize cognitive productivity.	375
[G11.2] When designing an interactive node–link diagram or road map, consider providing algorithm support for pathfinding if paths are complex.	403
[G11.3] In large data spaces containing small islands of critical information, consider enabling the user to add extra windows showing magnified areas of the larger space. This is especially useful for tasks that require frequent queries to compare patterns having more than three visual working memory chunks. This is a supplement to guideline G10.15.	412

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Index

Page numbers in *italics* indicate figures, tables and text boxes.

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