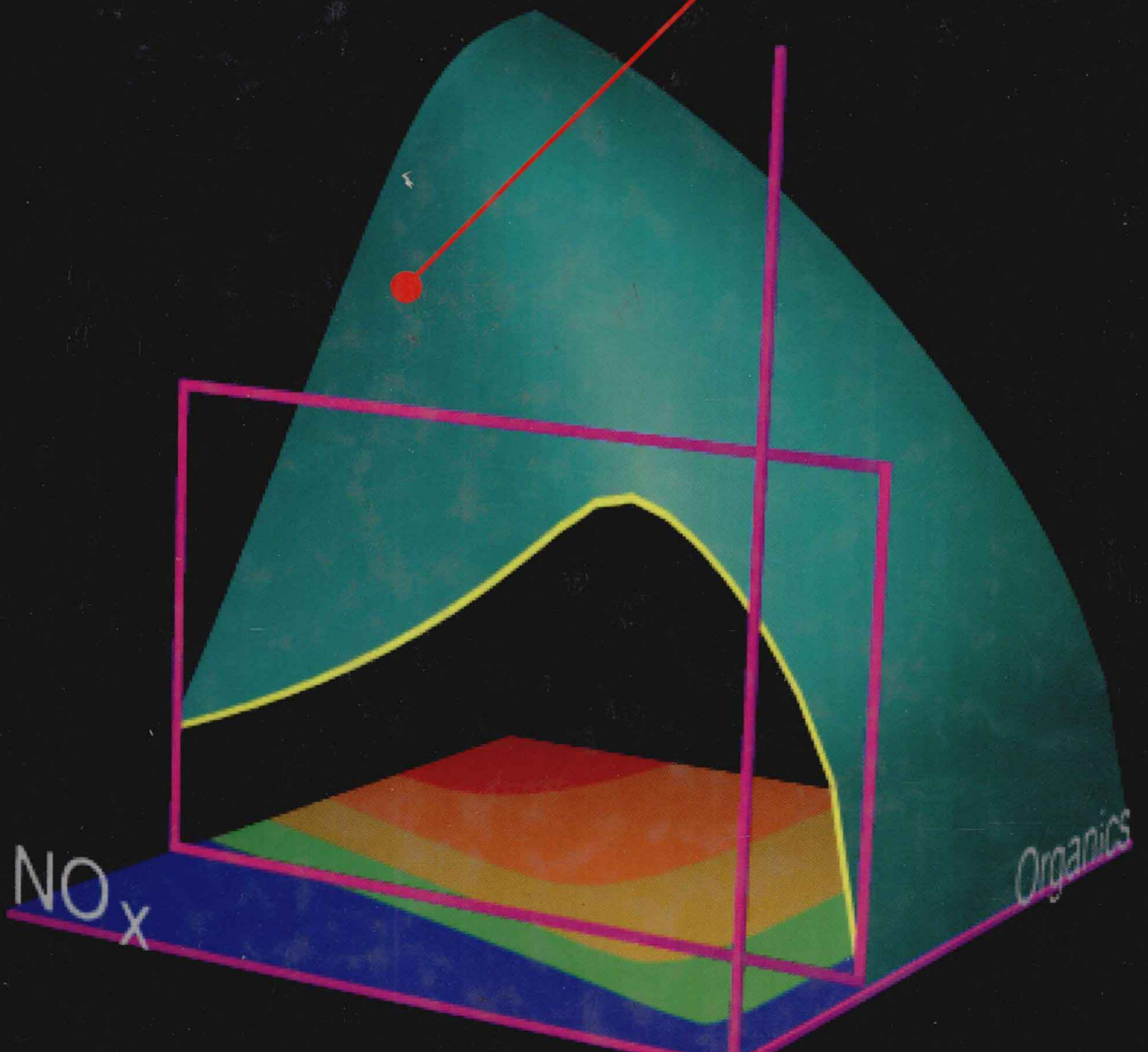
Visual Cues

Practical Data Visualization

Peter R. Keller   Mary M. Keller



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Library of Congress Cataloging-in-Publication Data

Keller, Peter (Peter R.)
Visual Cues / Peter and Mary Keller.
p. cm.
Includes bibliographical references and index.
ISBN 0-8186-3102-3
1. Science—Methodology—Handbooks, manuals, etc. 2. Engineering—Methodology—Handbooks, manuals, etc. 3. Visualization—Techniques—Handbooks, manuals, etc. 4. Computer graphics—Handbooks, manuals, etc. I. Keller, Mary.
Q175.K29 1992 — 92-23865
502.85'66—dc20 — CIP

Copublished by

IEEE Computer Society Press
10662 Los Vaqueros Circle
PO Box 3014
Los Alamitos, CA 90720-1264

IEEE Press
445 Hoes Lane
PO Box 1331
Piscataway, NJ 08855-1331

IEEE Computer Society Press Order Number 3100-04
IEEE Press Order Number PC0286-5
Library of Congress Number 92-23865
ISBN 0-8186-3101-5 (microfiche)
ISBN 0-8186-3102-3 (case)

Additional copies can be ordered from

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PO Box 3014
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IEEE Computer Society
13, avenue de l'Aquilon
B-1200 Brussels
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Ooshima Building
2-19-1 Minami-Aoyama
Minato-ku, Tokyo 107
JAPAN

IEEE Press
445 Hoes Lane
PO Box 1331
Piscataway, NJ 08855-1331

This book was acquired, developed, and produced by
Manning Publications Co., 3 Lewis Street, Greenwich, CT 06830

Copy Editor: David Lynch
Cover Design: Krzysztof Lenk
Book Design: Paul Kahn
Printed in Hong Kong

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Preface

Our longstanding interest in visualization and our many years of helping others use visualization has led to this book. We share our experience to demonstrate how the available visual tools can help you meaningfully depict your data. Other publications have described visualization use in specific disciplines, or have concentrated on analyzing how an algorithm produces an image. Those approaches appeal particularly to experts in those respective fields. In our work with scientists and engineers, however, we have found they almost always approach visualization pragmatically; their primary interest is in the application of available tools and techniques that can help explore, analyze, and communicate information about their data.

In accordance with our experience, *Visual Cues* shows by example the generic information that a visualization technique reveals about any data on which it is used. We have found that emphasizing what a technique reveals frees users to focus on what they want to see in their data independent of algorithm and discipline, and we believe this approach will work equally well for those in other disciplines.

We offer 150 examples that show effective techniques to use to analyze and present data. Some of the techniques may seem obvious to the computer scientist who daily works with visualization. Those in other disciplines will most likely find much that is new or not obvious. From the selection and descriptions of the images to the discussions on data visualization, output media, design, and use of color, our emphasis is on providing practical information to help you use visualization effectively and efficiently in your offices and laboratories.

We dedicate this book to our parents, who taught the value of completing the task.

PETER R. KELLER

MARY M. KELLER

Acknowledgments

Visual Cues has been accomplished with the encouragement, inspiration, and help of many. Peter credits the book's genesis to the support and encouragement he received from three of his former supervisors at Lawrence Livermore National Laboratory: John Horvath, Len Margolin, and Donald Vickers. They possessed keen insight into the direction of computer-graphics technology and its value to scientists and engineers. Each encouraged Peter's collaboration with scientists and engineers so that he might help identify unrecognized graphics needs and devise new graphics techniques to better aid their research. Because of those collaborations Peter realized that many expect to benefit from visualization without having to become visualization experts.

A source of inspiration was Minh Duong-van, a physicist at Lawrence Livermore studying the nature of chaos in a variety of application domains. Minh's contagious enthusiasm for discovering new meaning in data inspired Peter to develop visualization techniques that permit rapid data exploration and analysis and that quickly and visually "prove" a concept. This fast-paced collaboration led to the realization that graphic techniques could be considered entities, independent of the data, application, output medium, and stage of image construction.

We acknowledge the contribution of all who answered our request for examples of visualization. Without their help the writing of *Visual Cues* would have been much more laborious. Most respondents were the actual creators of the images they submitted; a few respondents recognized the significance of another's work in visualization and took time to submit an example, crediting the image creator. All individuals whose visualization examples appear in *Visual Cues* are listed alphabetically in Appendix G. Names of contributors also appear on the page with their visualization image.

During the writing of *Visual Cues* many people supported us by suggesting topics, submitting material, providing secretarial support, or reviewing the numerous drafts. We acknowledge: William Banks, Mark Blair, David Butler, Scott Carman, Kenneth Charron, Raymond Cochran, John Compton, Patrick Crowley, Michael Feit, Dorothy Freeman, Terry Girill, Kevin Gleason, Diane Governor, David Handeli, Christel Horten, John Horvath, Gene Ledbetter, Albert Miller, Amal Molik, Henry O'Brien, Patricia Parsens, Dan Patterson, Viviane Rupert, Joseph Sefcik, Thomas Thompson, Jaylene Tingley, Venkatesw (Rao) Vemuri, Donald Vickers, Claudia

Watkins, Steven Wehrend, Richard Williams, and George Zimmerman. A special thank you goes to Gary Shaw for his organization of the original book design requested by the publisher. This design was the foundation for the subsequent writing. We especially want to thank Marjan Bacé of Manning Publications for his support, guidance, and friendship throughout the development of *Visual Cues*.

Numerous people helped ensure high quality in preparation of the text, images, artwork, and design; we are especially grateful to Earl Aldrich, Rita Anderson, John Blunden, Mark Bussanich, Elizabeth Caires, Marjory Cantor, Lynn Costa, Gary Graff, Arlene Hee, Nancy J. Hill, Barbara Kahn, Paul Kahn, Christina Keller, Peter Link, David Lynch, Margaret Marynowski, and Kelly Spruiell.

Those who had a large but thankless part in reviewing all or parts of the final tome richly deserve our thanks: John Ambrosiano, Chris L. Anderson, Tom Bennett, John Blunden, David E. Breen, Stewart Brown, Robert W. Conley, Roger Crawfis, Said Elghobashi, Kirby Fong, Gary Graff, Beverly Hobson, William Hobson, Carolyn Hunt, Thomas Kelleher, Cynthia Keller, James Keller, Jackson Mayes, Umberto Ravaioli, Susan Schoenung, Nancy Storch, Roy Troutman, Richard Ward and , David Wells. We especially want to recognize Nelson Max for his technical review of the front chapters, carefully pointing out matters we had overlooked.

Any large organization has its maze of rules, regulations, and required approvals. We wish to thank those from the Lawrence Livermore National Laboratory management and staff who helped guide us through the maze, including Edward Bodily, Robert Borchers, Dennis Braddy, Scott Buginas, William Dunlop, Richard Dyer, Rex Evans, Bill Fulmer, Robert Lormand, Charles McCaleb, Coralyn McGregor, Charles Miller, Leland Minner, Ronald Natali, Dale Nielsen, David Nowak, Michael Pratt, Gerald Richards, Jack Russ, Diana Sackett, Henry Sartorio, Marty Simpson, Sandra Sydnor, and John Verity. We especially want to thank Ann Abers, William Masson, and Diana (Cookie) West whose knowledge and help were indispensable to our success.

We also want to thank other friends and coworkers who helped more than they probably realize. Their interest and occasional query, "How is it going?" or their invitations that provided refreshing breaks from the writing routine were just the tonic to help us maintain the momentum. And we cannot omit Albert "Thor" von Rott Hutte, our ever-present, always willing, but undemanding diversion and reality check.

Portions of this work were performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract No. W-7405-Eng-48.

Contents

Introduction

The ever-increasing power of computers, which enable the generation and processing of vast amounts of data, creates an imperative for techniques that facilitate exploration, analysis, and communication of that data. More and more, that imperative is being effectively answered by using the capability of computers to present data in graphical form. Indeed, the popular media often carry colorful computer-generated images that communicate data in ways understandable to the non-expert.

The proliferation of such colorful images implies that meaningful visualization of data is routine in laboratories and offices. Although such published examples certainly provide evidence of what is possible, the reality is that how to achieve the possible is not widely known. The description of such images usually emphasizes the application, discussing what is being learned about the data; the techniques that accomplish the image are secondary and presented in terms specific to the application.

Such discussion, though certainly valid, hides the fact that the techniques could be used with a whole range of applications, disciplines, data structures, and data formats. *Visual Cues* asserts that although each discipline has its own data, the kind of information that specialists want to depict and convey about data is often universal. Physicists may want to reveal the structure of fluid flows, medical doctors may want to reveal the structure of a malignancy, geologists may want to reveal the structure of oil deposits, and meteorologists may want to reveal the structure of a tornado. Of the many techniques available that reveal structure, most can usually be applied to any data regardless of application, discipline, structure, or format. In our examples, we emphasize visual cues that communicate information independent of any specific hardware products or software techniques; most tasks could be accomplished by any of several products or techniques.

From our experience we know too that specialists usually want to focus on their field of study and have no desire to become computer graphics experts in order to use visualization. Therefore, we omit the details on how visualization algorithms are derived and instead emphasize the results that can be obtained with algorithms. Our many examples present a broad spectrum of available visual cues, most of which can be created by one of the many visualization algorithms already available. Our examples are intended to enable generation of a meaningful image by linking the knowledge of a discipline and the knowledge of visualization. Having examples that show which visual cues reveal which information can eliminate guesswork and may also suggest other meanings to look for in the data.

Purpose

Our purpose in writing *Visual Cues* is to help make the possible doable—to put visualization capability in your hands by:

- Presenting a large collection of visualization images, some of which may relate to your current work.

- Describing generically the visualization techniques used to construct images in a variety of disciplines.

- Emphasizing the kinds of information revealed by a visualization algorithm rather than details about the algorithm or the application.

- Providing a handy reference work you can peruse when actually looking for a visualization technique to illustrate data.

- Introducing a methodology for selecting a visualization technique.

- Providing basic information about output media, image design, and color, knowledge of which is vital in creating an effective image.

Scientific visualization is a broad, rapidly evolving field filled with complexity. We use our eyes to visualize the world day after day—isn't it incongruous that scientific visualization can be so complicated? In *Visual Cues*, we generally hide the complexities and instead focus on practical aspects that you can apply to data in your discipline.

Audience

Visual Cues is addressed to several audiences who can be generally classified as either the consumers of visualization or the facilitators of visualization. We include as consumers all those who benefit from the construction and viewing of an image of their data. Physicists, engineers, medical doctors, geologists, physiologists, and statisticians are examples of some of the many who might be so categorized. Facilitators of visualization are the "visualization specialists" and include, among others, computer scientists, systems analysts, artists, computer graphics programmers, and designers. Visualization specialists help consumers analyze data, perhaps by programming algorithms, suggesting image layout and design, applying knowledge of the physiology of color, or using any other combination of talent that helps bring out the meaning hidden in the data.

Visual Cues may be especially helpful for those in a research setting, who often have voluminous, novel, or poorly understood data to explore, analyze, and present. Our experience indicates that researchers need to visually validate their data, trying many representations to determine which parts of the data deserve greater study and analysis. The analysis phase tests one or more hypotheses; the results are then communicated with a visual emphasis that highlights the results. Such needs may require the use of many visualization techniques before the researcher discovers how to proceed with the data. The many examples in *Visual Cues* can be a resource for techniques to use when visually exploring data.

You do not have to be directly involved in visualizing scientific data to find *Visual Cues* helpful. Managers of organizations that need visualization will find a survey of visualization techniques that could help determine appropriate tools for their staff. Commercial artists and computer artists will find *Visual Cues* a practical source for ideas to create their artistic message. *Visual Cues* can also serve as a convenient compendium of examples of different techniques for teachers and students to use for discussion and comparisons. The book can be perused for ideas, studied for details, or used as a communication tool by anyone who sees the value of the computer as a visualization medium and communication tool.

Structure

Visual Cues has two instructive sections, seven appendices, a glossary, and a general index. In Section I, we draw on our experience and offer tips for selecting visualization techniques and designing images to clearly communicate the intended meaning. Section II consists of images using visualization techniques from contributors worldwide in disciplines as different as medicine and astrophysics and computer art. Throughout the book, the images in Section II are referenced by a boldface number, for example, **11-9**. Most of these images suggest practical ways you might use visualization to understand or communicate something about data. We have selected them not because they are flawless, but because they illustrate a technique, an approach, a solution for visualizing data that is a bit different from each of the other images. The diversity is meant to stir the imagination as well as to show what is possible. In our accompanying descriptions, we give the technique for deriving each image, including the visual cue or cues that help communicate meaning hidden in the data, the specific application using the technique, the hardware and software that created the image, hints about using the technique, and cross-references to related or contrasting examples in *Visual Cues*.

Each appendix provides a point of entry to the book. Appendixes A and B introduce a methodical way of locating possible techniques that some consumers of visualization have found useful. The methods emphasize the advantage of determining the meaning to be derived from data before data are visualized, instead of plotting data and then looking for meaning. Other appendixes list the major goal of image; number of variables; discipline (such as solid state physics, fusion engineering, or astronomy); hardware and software used; and contributors.

We have designed *Visual Cues* so that you can obtain a quick overview or detailed information. Skimming the succinct summaries and captions next to the images in Section II can provide you with global knowledge of visualization and how to use it. More careful reading of the sections and Appendixes A and B can teach you the basic tricks of the trade and direct you to specific techniques for accomplishing your visualization goal.

Vocabulary

In the extensive glossary we define many technical terms that appear in *Visual Cues*. But as in many new disciplines, the meaning of some common words and phrases can vary depending on the definer's emphasis or on the hardware or software product. We clarify our use of a few such words.

Scientific visualization in this book means the study, development, and use of graphic representations and supporting techniques that facilitate the visual communication of knowledge—that make computer images speak to us.

Visualization means the bringing out of meaning in data.

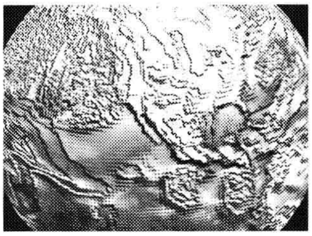
Data means any form of number created by or input to a computer, including scientific data, engineering data, medical data, statistical data, computed data, measured data, scanned data, simulated data, approximated data, smoothed data, sparse data, and voluminous data. Data are simply the numbers the computer knows about.

Technique is the method, rule, step, procedure, or algorithm used in the construction of an image. Among these are data-representation techniques, layout and design techniques, visualization algorithms, data-conversion algorithms, and procedures for creating or constructing contextual cues.

Background

We gleaned the images in Section II from more than 1000 examples submitted by more than 100 respondents to more than 1000 requests sent to participants in major visualization conferences, schools offering degrees in computer graphics and related disciplines, and major vendors of visualization hardware and software. We chose these sources because we wanted to include mainly examples of current work. Each contributor was asked to briefly describe the image. From these initial submissions, we selected images that represented a broad cross-section of disciplines and techniques and then requested more specific information from each contributor. We rewrote that information to achieve an even standard of exposition and returned that writeup to the contributor for technical review. The complete book was then reviewed by several experts, which led to further refinements. The images themselves were collected on photo, viewgraph, printer output, and a various electronic file formats. To create a uniform graphical appearance, we converted all formats to Apple Macintosh TIFF file format. Adobe Photoshop was used to crop, size, and perform minor editing of the images for consistency and clarity. Text was composed on an Apple Macintosh IIcx, with Microsoft Word. Word and TIFF files were imported to Aldus Pagemaker for design and layout and to produce the color separations for printing.

Section I
Effective Visualization



Computer hardware and software are making the visualization of numerical data increasingly easy and affordable. With these improvements also comes the capability of using more and better visual cues to reveal and depict the meaning of data. Now it is possible to impart greater meaning to visualization by using visual cues that illustrate motion, suggest relationships, or relate data to the phenomenon being studied. The challenge now is learning how to efficiently and effectively use these abundant resources and tools to reveal the meaning in the data.

We believe that successfully meeting this challenge first requires determining what meaning is to be conveyed in an image and then choosing the technique that best depicts the meaning. Another important—though often downplayed—aspect of meeting this challenge is managing such image components as size, placement, color, and labeling to ensure that an image clearly conveys the intended meaning.

Attention to such components is even more important when presenting an image to an audience. Besides providing tools for exploration and analysis, visualization offers a powerful tool for communicating meaning to others. For years, commercial advertising has used graphic presentations to sell products. Now scientists and engineers and others are beginning to recognize that visualization greatly enhances their efforts to gain support for research, to help them get needed funding. A visualization that clearly conveys the meaning of data not only helps explain the researcher's ideas but also casts a glow of credibility and capability.

In this section we draw on our experience in helping scientists and engineers meet the challenge of producing meaningful images from their data. We present our method for selecting visualization techniques. We also offer guidelines for selecting an output medium, designing an image, and handling color. We point to many examples in Section II to illustrate our advice. We are your guides as you construct effective images and avoid problems that can obscure or distort the information in your data. Many of the details we cite are easy to overlook, but ignoring them can result in a confusing or an unintelligible image.

Visualizing Data: Focusing on an Approach

The very abundance of visualization techniques can make selecting the one most appropriate for bringing out the meaning in data a perplexing search—a difficult, frustrating, and time-consuming aspect of visualization. If your thought process is like ours, you most likely rely first on experience. If nothing appropriate suggests itself, you may turn to other convenient sources: programs that colleagues are currently using or a new technique a friendly programmer offers. In each instance, you study the resulting image for any useful information it may reveal. This reflexive "try, then study" approach may eventually yield an image that reveals the meaning in the data, but it is just as likely to yield an image that is pretty but useless.

A methodology is needed for selecting visualization techniques, but the nascent discipline of scientific visualization does not yet have pat formulas for selecting appropriate techniques. A focused approach like that outlined in the following paragraphs is one we have found successful. It is meant to eliminate obstacles that may obscure valuable techniques.

In describing this approach, we have sometimes used a broad brush to depict a complex subject. Wherever we introduce a simplified view, we also refer you to texts with more detailed discussion. Our goal in simplifying is to quickly put an image of your data in your hands by shielding you from detail while building your understanding of scientific visualization.

The main points in our approach are to:

• Identify the visualization goal: We identify the meaning we seek in the data before we begin to construct an image. Knowing the goal, we may recognize new sources of techniques; meanwhile we have a focus for determining if a prospective technique is likely to reveal the meaning.

• Remove mental roadblocks: We regard data as nothing more than numbers bearing information to be visualized. When we think of data as belonging to some application or having some structure, we unnecessarily limit ourselves in imagining possible techniques.

• Decide between data or phenomena: We distinguish between data-representation and contextual-cue techniques. Data representation shows the data values independent of the phenomenon; the viewer must deduce the relationship to the phenomenon. Contextual-cue techniques relate the data values to the phenomenon being studied and add meaning to the visualization. Deciding whether data or phenomena are the focus further refines the visualization goal.

Identifying The Visualization Goal

Beginning data visualization by first identifying the visualization goal may give some pause, but we believe identifying the goal is the cornerstone in constructing an effective image. The goal is the meaning you hope to derive from the image, and, if appropriate, the meaning you want to communicate to others about your data. Identifying what you want to learn helps you select techniques that will produce an image communicating that meaning if the data support it. Just as a builder must know the building plan to select the correct construction materials, so too should you identify the desired result before proceeding to select techniques for visualizing data.

Usually data visualization consists of exploration, analysis, and then presentation—if the visualization is used to communicate with others.* Identifying the ultimate visualization goal may be evolutionary, reflecting the stage in the visualization process in which we are involved. Exploration, the searching of data for new relationships, usually means many trial-and-error data representations and requires interactive adjustment of data or image. Analysis, the study of known relationships among data, may require metrics or other precise means for comparison. Analysis and exploration are generally accomplished by one person or a few, and images that result need not be pretty or refined; they may even be unlabeled and, hence, meaningless to someone not familiar with the data or problem. Presentation is the "publication" of data for the benefit of others; the image should be aesthetically appealing, properly annotated, and intelligible.

How do you identify a visualization goal? Regardless of where you are in the visualization process, you need to ask such questions as Why am I looking at these data? What is important about the data? Am I comparing, associating, locating, verifying, finding, ranking, searching? What do I hope to learn? What do I want the image to say? What do the data prove? What do I expect the data to prove? In the exploration stage, the goal may be less focused than in the analysis and presentation stages. See Appendixes A and B for possible goals.

In fact, you are already identifying visualization goals, though perhaps subconsciously, when you input data to a graphics utility you have used for similar data. The unstated goal may be, "Compare this image with the prior image." Or this idea might be at the back of your mind, "If it is wrong, I will know it," meaning, "Verify the correctness," or again, "Compare this image with the correct image." The more you can focus the goal, however, the more effectively you can construct images. **11-1** provides a good example of how the visualization goal affects technique selection. Both images are constructed from the same data, but because each image uses a different color palette, each depicts different information. In **11-1,** Figure A, the goal may have been "reveal shape," and in **11-1**, Figure B, the goal may have been "examine structure." Identifying the goal permits the selection of the appropriate color palette. The more specific the goal, the better focused and more useful the visualization.

Removing Mental Roadblocks

Here again, we suggest an approach that may seem untraditional. Our experience with scientists and engineers leads us to believe that many have been conditioned to regard data as some entity with inviolate properties. This rigid thinking may

* Some visualization specialists distinguish types of visualizations by the terms *personal, peer,* or *presentation.* We prefer to distinguish types of visualization by the terms *exploration, analysis,* and *presentation,* which emphasize the functional aspects of visualization.

narrow the choice of techniques. We urge you instead to think of data only as numbers—numbers that a computer knows about. If data are only numbers, you can then consider any image-construction technique for the data. Treating data thus eliminates artificial constraints imposed by associating data with their origin (discipline or application), format or structure, or dimension. Instead you can consider any technique that will reveal the meaning in your data. This approach also diverts you from the common practice of using a familiar representation and then trying to figure out what you see in the representation.

Eliminating Constraints of Discipline and Application

Thinking of data as medical, mechanical-design, fluid-flow, oil-industry, satellite, or earthquake may focus you only on the image-construction techniques already used in that discipline. Techniques from a different discipline, however, might better represent data or might suggest modifications to the technique you are using. For example, if you have engineering data, you should not automatically use a CAD/CAM/CAE package for visualization. **2-4** and **2-11** visualize complex engineering data with general-purpose visualization techniques. **2-4** uses color and 3-D to visualize tensor qualities. **2-11** also chooses color and 3-D and adds glyphs. Of course, using a technique associated with the discipline from which your data come is often entirely appropriate. The important point is that you should select a technique because it produces the result you want, not because it is traditional in a discipline. Exploring the visualization techniques useful in other disciplines can enhance your ability to find those useful for your own data.

Eliminating Constraints of Format and Structure

Data-representation techniques do have specific format and structure requirements, and data in each discipline tend to be collected in specific formats and structures. For example, much of mechanical engineering data are geometry data, medicine data are image or scanned data, satellite data are signal (time-history) data. Therefore, selecting a technique with the same format and structure requirements that your data have seems logical. The data fit easily into the conventional utility requirements. But if the familiar or usual technique does not best depict your data, you should consider other techniques and not be deterred because your data are in a format or structure unacceptable for use with that technique. Data-conversion algorithms allow you to convert data to fit different requirements, and therefore to use other available techniques. It is usually easier to convert data to a technique to which you already have access than to write a new, equivalent technique.

Here's an example: you may think that an irregular (nonrectangular) array of real numbers cannot use imaging software because such software generally requires a rectangular array of integers from some image-scanning device. It is easy, however, to change the format of an irregular array from real to integer, and its structure, too, is easy to approximate with a rectangular array. The converted array can then use imaging software.

Among the images that use data conversion in *Visual Cues* is **8-4**, an example of how data with one structure can be converted for use with an algorithm that requires a different structure. An algorithm generates a 2-D slice of data through a 3-D pressure field. The 2-D slice is then pseudocolored by a conveniently available algorithm and merged with the 3-D model to relate the data to the model. **10-5** provides another example of structure conversion. The data, originally represented on a square mesh, were converted to an irregular triangular mesh to take advantage of increased rendering speed.

Other algorithms that convert or modify data take randomly positioned data and convert them to regularly positioned data, minimize noisy data with smoothing algorithms, or create planar data by passing a plane through a volume of data.

You can find algorithms for data conversion in numerical analysis and computer graphics journals. Also, each of these four books describes a few conversion algorithms: Andrew S. Glassner, ed., *Graphics Gems* (San Diego: Academic Press, 1990); James Arvo, ed., *Graphics Gems II* (San Diego: Academic Press, 1991); David Kirk, ed., *Graphics Gems III* (San Diego: Academic Press, 1992); and William H. Press et al., *Numerical Recipes* (Cambridge, Eng.: Cambridge University Press, 1986).

We urge you not to hesitate to convert data to a different format or structure because you fear that conversion may introduce errors in approximation. Such errors, though harmful if the data are to be used for continued simulation, generally cannot be discerned in the data representation of an image. Ignoring conversion errors, especially in the exploration phase of visualization, encourages rapid evaluation of techniques. Our experience shows that positional errors introduced are small and errors for data values even smaller. Whether these errors are tolerable depends, of course, on the application. An architect's plan for uniform air temperature in a small room is less critical than a surgeon's plan for risky, delicate surgery. Generally, though, errors are tolerable during exploration but must be accounted for in analysis.

Data conversion can be a complex, tedious issue that may have to be addressed for accurate analysis. But if you find a visualization algorithm you want to use, we suggest that you convert your data to the algorithm's input format and structure rather than rewrite visualization algorithms to work with the format or, worse yet, forgo constructing a meaningful image because you think your data cannot be used with the algorithm.

Eliminating Constraints of Dimension

Thinking that the representation's dimensions or number of variables must be the same as those in your data can also channel your thinking and eliminate useful techniques. For example, in selecting a representation technique you can often treat a 2-D scalar field and a (single-valued) 3-D surface as the same kind of data set. You can then use the same visual techniques for both kinds of data. **7-3** illustrates how a 2-D scalar field can be represented as a 3-D surface. Conversely, a 3-D surface can be projected on a plane and the values treated as 2-D, a technique commonly seen in U.S. Geological Survey maps, for which data on elevation are projected to a plane that is then represented as a contour map. With either data set, the 2-D representation can be a contour plot or pseudocolor plot, and the 3-D representation can be a shaded surface. The shaded surface could also include isolines and color.

Nor should the number of variables limit your representation choices. A variable is said to be a dependent if it is a function of another variable (called an independent variable). In the equation $y = f(x)$, x is the independent variable and y is the dependent variable. You can use the common x-y scatterplot to study the relationship. If you have a two-variable data set x and y (say temperature and humidity), where x and y are measured at the same point, you have two variables. There is no defined relationship. You can visually determine if there is a relationship, though, by using the same x-y scatterplot as you used to show the relationship between the independent and dependent variables. In using a visualization technique, it often does not really matter whether you have two variables or one dependent variable