1. Future Challenges and Unsolved Problems (in Human-Centered Visualization)

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Abstract

The visualization community is currently in a phase of self evaluation and retrospection. Almost 20 years after the publication of the National Science Foundation (NSF) report entitled, "Visualization in Scientific Computing", by McCormick, DeFanti, and Brown (1987), visualization researchers are looking back–identifying those visualization problems that have been solved, and looking forward to the challenges and unsolved problems in the next 20 years. In light of this shift in direction, we survey and present a selected list of future challenges and top unsolved problems in visualization with an emphasis on human-centered visualization. The list presented here surveys and categorizes what we consider the most important future challenges into three classes: human-centered, technical, and financial. The result is useful for gaining insight into both past and future directions in visualization research and provides a provocative forum for discussion.

Keywords: human-centered visualization, information visualization, top challenges, unsolved problems, survey

1.1 Introduction

Self-criticism, evaluation, solved and unsolved problems, and future directions are wide-spread themes pervading the visualization community today. The top unsolved problems in both scientific and information visualization was the subject of an IEEE Visualization Conference panel in 2004 [48]. The future of graphics hardware was another important topic of discussion the same year [25]. A critical evaluation of usability and utility of visualization software was also the focus of a recent panel discussion [17]. The topic of how to evaluate visualization came up again two years later [20, 66]. Chris Johnson recently published his list of top problems in scientific visualization research [22]. This was followed up by report of both past achievements and future challenges in visualization research as well as financial support recommendations to the National Science Foundation (NSF) and National Institute of Health (NIH) [23]. That report is the result of two workshops that took place in the Fall of 2004 and Spring of 2005 on visualization research challenges and also includes input from the larger visualization community. C. Chen recently published the first list of top unsolved information

visualization problems [5]. Future research directions of topology-based visualization was also a major theme of a workshop on topology-based methods [18, 50].

These pervasive themes are the result of shift in visualization research. They coincide roughly with the 20^{th} anniversary of what is often recognized as the start of visualization in computing as a distinct field of research [42]. Consensus is growing that some fundamental problems have been solved and a re-alignment including new directions is sought. This shift is characterized by rapid increases in computing power with respect to both the CPU and the GPU as well as swift decreases in the cost of computing hardware. Advances in display technology and networking have also made visual computing more ubiquitous. Cell phones, personal digital assistants (PDAs), other hand-held devices, as well as flat panel displays are now commonplace.

In accordance to this redirection, we present a more comprehensive list of top unsolved problems and future challenges in visualization with an emphasis on human-centered visualization. Our list draws upon and summarizes previous related literature, previous chapters, discussions in the visualization community, as well as our own first hand experiences. We recognize the subjective nature of the topic and thus our presentation aims to survey and complement previous related research as well as introduce some of our own personal view points. Our survey of related literature identifies several future challenges and then classifies each into one of three categories: human-centered, technical, and financial, as follows:

Human-Centered Challenges.

- *Interdisciplinary Collaboration*: Communication and knowledge transfer between the visualization community and application domain experts is very important (and currently lacking, Section 1.2.1).
- *Evaluation of Usability*: Human-centered evaluation of interfaces, metaphors, and abstractions that appeal best from an HCI perspective will play an important role (Section 1.2.1).
- *Finding Effective Visual Metaphors*: Assigning an intuitive geometry to non-spatial data promises to remain an important challenge (Section 1.2.1).
- *Choosing Optimal Levels of Abstraction*: From an implementation point of view, choosing an optimal level of data abstraction is arbitrary. Finding the optimal level of abstraction from a user's point of view is non-trivial (Section 1.2.1).
- *Collaborative Visualization*: The art and science of sharing interaction and visualization between multiple user simultaneously is still in its infancy, rich with unsolved problems and future challenges (Section 1.2.1).
- *Effective Interaction*: Much work still remains in developing intuitive interaction techniques, especially in the field of virtual reality.
- *Representing Data Quality*: Not all data is equal. The quality of data can vary according to several different factors. Such variance provokes several research challenges (Section 1.2.1).

Technical Challenges.

– *Scalability and Large Data Management*: The size of data sets continues to grow faster than the software used to handle it, a trend that promises to continue in the future (Section 1.2.2).
– *High Data Dimensionality and Time-Dependent Data*: The complexity posed by data with many attributes is a challenge that every visualization researcher is familiar with (Section 1.2.2).
– *Data Filtering*: Ever growing data sets demand more methods and technologies needed to filter out subsets of the data that are deemed interesting by the user (Section 1.2.2).
– *Platform Independent Visualization*: Although we may want to show the same image to several different people, very rarely do two users have the exact same hardware and software setup (Section 1.2.2).

Financial Challenges.

– *Evaluating Effectiveness and Utility*: Not all visualizations and interaction methodologies are equally effective and useful. Deciding in which technologies to invest both time and money will certainly challenge researchers in the future (Section 1.2.3).
– *Introducing Standards and Benchmarks*: While many other branches of computer science feature standards, e.g., networking protocols and database designs, visualization is still lacking standards at many different levels (Section 1.2.3).
– *Transforming Research Into Practice*: In order to contribute to society at large, successful research results must find their way into practical applications (Section 1.2.3).

This is the first such list in visualization to present financial challenges in such an explicit manner–in a category on their own. Our survey of top unsolved problems attempts to provide more depth than previous, related articles. We also do not abide by the common, arbitrary restriction of limiting the number of unsolved problems and future challenges based on the number of fingers we have.

1.2 Classification of Future Challenges and Unsolved Problems in Human-Centered Visualization

Before going into depth with respect to related research on the topics of unsolved problems and future challenges in information visualization, we provide a brief overview of important and influential related literature and events.

For a look back at human-centered visualization research, we refer the reader to Tory and Möller [60]. Related literature describing unsolved problems dates back over 100 years in other disciplines. David Hilbert's list of unsolved problems in mathematics [1] was presented at the Second International Congress in Paris on August 8, 1900. Lists of unsolved problems more closely related to visualization date back to 1966 with Ivan Sutherland's list of unsolved problems in computer graphics [56]. Another list of unsolved problems in computer graphics was presented by Jim Blinn at the ACM SIGGRAPH conference in 1998 [2].

[1] Available online at:
`http://mathworld.wolfram.com/HilbertsProblems.html`

In 1994, Al Globus and Eric Raible published one of the first self-criticisms of the visualization community [15]. We feel that such criticism is closely related to challenges and unsolved problems because common visualization flaws are highlighted. The identification of non-ideal practices must occur before such problems can be corrected. Multiple themes occurring in this list serve as precursors to material that later appears in visualization challenges literature. Self-criticism is also presented by Bill Lorensen [40].

The first list of future challenges in visualization specifically, was published in 1999 by Bill Hibbard [19]. In fact, Hibbard's list is very human-centered. The two major themes throughout his presentation are: (1) the interface between computer and people and (2) the interface between people and other people created by a combination of computer networking and visualization. Challenges are based on adapting computer capabilities to correspond as closely as possible to human capabilities and perception.

Fifteen years later, Chris Johnson published his list of top visualization research problems in scientific visualization [22]. His work includes topics such as: more interdisciplinary knowledge transfer, quantifying effectiveness, representing error, perception, utilizing novel hardware, global vs. local visualization, multi-field visualization, feature extraction, time-dependent visualization, distributed visualization, visual abstractions, and visualization theory. These themes are brought up again and elaborated on in the follow-up NIH/NSF Visualization Research Challenges report [23] published in 2005 and 2006.

Chaomei Chen published the first list (to our knowledge) of top unsolved information visualization problems [5] in 2005. Themes include: usability, knowledge of other domains, education, evaluation of quality, scalability, aesthetics, and changing trends. Many of these topics are discussed in more detail in a book by the same author [4].

Thomas and Cook have also recently published a book describing the future agenda in the emerging field of visual analytics [59]. Chapter one presents the "Grand Challenges" for researchers in visual analytics. Themes include: data filtering, large data sets, multiple levels of scale, cross-platform visualization, collaborative visualization, visual metaphors, evaluation, and system interoperability. These grand challenges were presented in Jim Thomas' Keynote Address: "Visual Analytics: a Grand Challenge in Science–Turning Information Overload into the Opportunity of the Decade", at the IEEE Information Visualization Conference 2005 in Minneapolis, Minnesota.

For completeness, we also note that University of North Carolina, Charlotte is hosting a "Symposium on the Future of Visualization", which took place 1–2 May, 2006.

Each literature source or event mentioned here influences our survey of future challenges and unsolved problems. Many issues pervade each list however terminology may differ. We incorporate not only previously published literature but also our personal experiences, view points, discussions with other researchers, and reviewer feedback. Indeed our list of grand challenges both overlaps and diverges from previous view points. Diverging on some topics serves to spark further discussion and thought.

1.2.1 Human-Centered Challenges

Here we elaborate on the literature and events addressing top future challenges and unsolved problems in visualization research, starting with those focused on human-

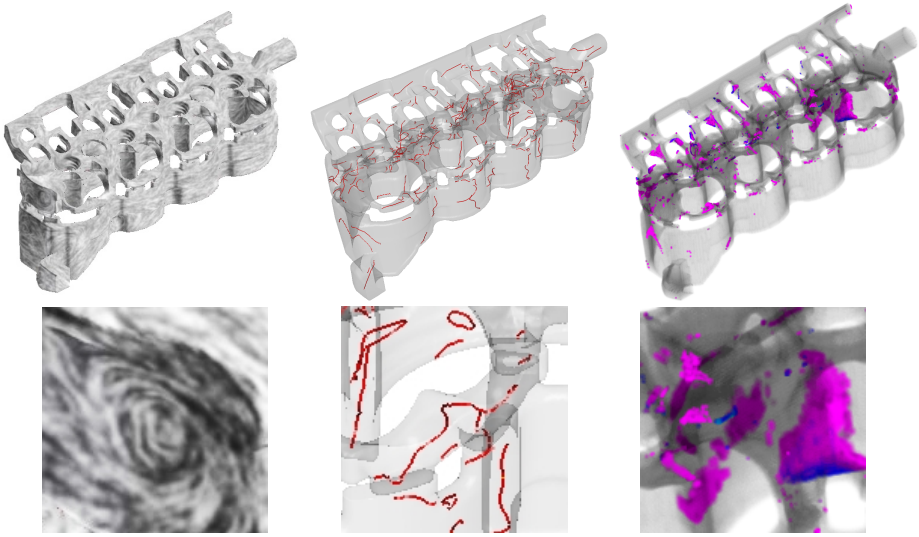

Fig. 1.1. The visualization of CFD simulation data from a cooling jacket: (left) texture-based flow visualization applied to the surface, (middle) semi-automatic extraction and visualization of vortex core lines using the moving cutting plane method [61] and, (right) a feature-based, focus+context visualization showing regions of near-stagnant flow, specified interactively. Each snap-shot is accompanied by a close-up. This work was the result of a collaboration between visualization researchers and mechanical engineers [34].

centered themes. The literature survey is organized by the future challenges and unsolved problems themselves. For each topic, the reader can find references to previous literature that addresses it. We note that most of the future challenges contain elements from all three categories we have chosen for our grouping: (1) human-centered with a focus on people, (2) technical with a focus on computing, and (3) financial with a focus on money. Thus we have classified the top unsolved problems where we feel the challenge mainly lies.

Challenge #1: Interdisciplinary Collaboration. Visualization research is not for the sake of visualization itself. In other words visualization is ultimately meant to help a user, i.e., someone normally outside the visualization community, gain insight into the problem they are trying to solve or the goal being sought after. Thus visualization researchers must communicate with practitioners in other disciplines such as business, engineering, or medicine in order to understand the problems that other professionals are trying to solve. This requires communication across more than one discipline. The disciplines may even be closely related, e.g. information and scientific visualization. Johnson called this problem “thinking about the science” [22]. It is also an opinion expressed strongly by Bill Lorensen [40]. As a concrete example, if a visualization researcher is writing software to visualize computational fluid dynamics (CFD) simulation results, it is best if the researcher collaborates with a CFD expert or a mechanical engineer. A CFD practitioner generally has s set of expectations from their CFD simulation results. Understanding these expectations requires interdisciplinary communication (Figure 1.1).

Any researcher who has attempted to collaborate with a practitioner in another discipline knows how difficult this challenge can be. Engineers, doctors, business people, etc., are neither paid nor required to communicate with a visualization researcher. If a professional is not interested in visualization, they may lack motivation to collaborate. Also, differences in domain-specific terminology must be overcome. Researchers at the VRVis Research Center have a considerable amount of experience with this problem. The VRVis Research Center, conceptually, acts as a transfer-of-knowledge bridge between the university and industry sectors in Austria. The vision of their research center is to bridge the gap between universities and industry by sharing knowledge and collaborating. Recently, they have been conducting interdisciplinary research with engineers from the CFD community [34, 38]. The results of their work were presented to both the visualization community at the IEEE Visualization Conferences and to the CFD and engineering analysis community at the NAFEMS World Congress [35]. When talking to the engineers at the NAFEMS conference, the attendees they spoke with were not aware of the existence of a visualization community. There were no other visualization researchers that they were aware of at the conference. And we see few practitioners visiting the IEEE Visualization of IEEE InfoVis Conferences.

Interdisciplinary collaboration can be very challenging. Generally, the motivation for such communication with practitioners could be strengthened. However, we do see signs of progress in this area. More quality, application-track papers have been published in recent years. We also note the emergence of the first Applied Visualization Conference (AppliedVis 2005) that took place in Asheville, North Carolina in April of 2005 (more information available at `http://www.appliedvis.org`). This topic was also a subject discussed in a recent panel discussion [58] as well as a recent research paper [66]. The Topology-Based Methods in Visualization Workshop 2005, (more information can be found at `http://www.VRVis.at/topo-in-vis`) had participants from both industry and academia.

Challenge #2: Evaluation of Usability. Software usability is a top challenge on most lists of future research directions, e.g., see Chen, challenge number 1–"Usability" [5] and Johnson, challenge number 2–"Quantify Effectiveness" [22], including Ivan Sutherland's list from 1966 [56]. Usability and evaluation are themes featured on virtually every visualization conferences' call for participation (CFP). Evaluation, perception, and usability are often topics featured in visualization conference panels [13, 17, 20, 43]. The ACM conference on Human Factors in Computing Systems (CHI) is well known and attracts thousands of visitors every year. Yet, the vast majority of visualization research literature does not the address human-computer interaction. New visualization techniques and systems rarely undergo any usability studies. But user-centered software design is central to the wide-spread use and success of any application (Figure 1.2).

In our experience, visualization researchers are often skeptical with respect to the topic of human-centered evaluation. Some factors contributing to this perception may include:

- *Time Consumption*: User studies are viewed as very time consuming and error prone.
- *Design Challenges*: Those with experience can agree that designing an effective user study can be very challenging [29, 37]. Visualization systems can be very complex

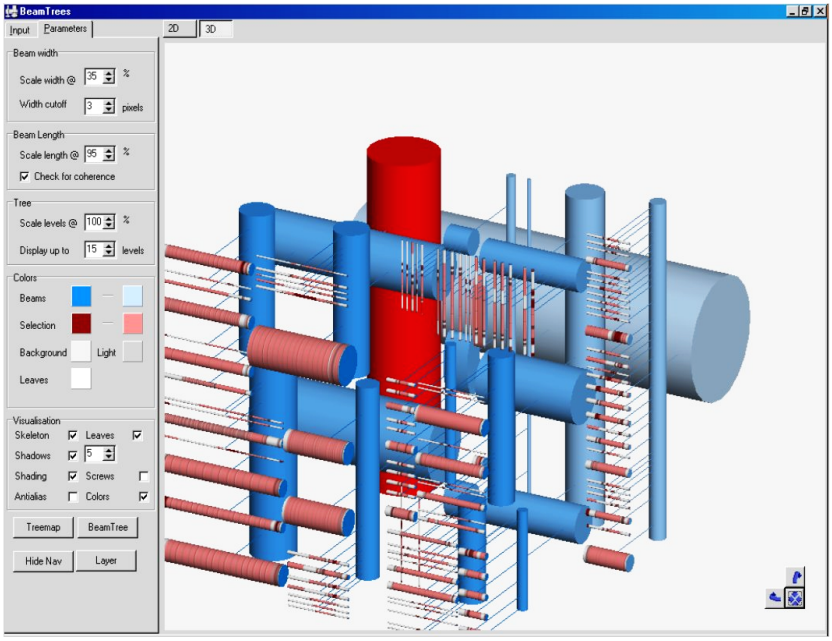

Fig. 1.2. BeamTrees were evaluated for along side other tree visualization systems [26]. *Image courtesy of Alfred Kobsa.*

and designing a user-study that isolates individual interactions and variables in an effective manner is difficult.
– *Design Literature*: Literature addressing effective user study design, although exists [29, 68], is generally lacking, especially in visualization.
– *Implementation*: Visualization techniques are generally difficult to implement. Thus, implementing more than one algorithm in order to evaluate multiple approaches is problematic.

The usability challenge has a long history and promises to remain an unsolved problem for the foreseeable future. Thus we consider this area to be rich with future research.

Challenge #3: Finding the Most Effective Visual Metaphors. Assigning a geometry to inherently non-spatial, abstract data can be problematic (see Figure 1.3). (See also challenge number 9 on Hibbard's list [19], challenge number 14, "Visual Abstractions" on Johnson's list [22], and Chapter 3–"Visual Representations and Interaction Techniques from Thomas and Cook [59]) A wide range of information visualization techniques have been introduced over the years to address this challenge. Some examples include: focus+context methods like fisheye views [12], the use of hyperbolic trees [30, 31], perspective walls [41], table lenses [46], parallel coordinates [21], cone and cam trees [49], collapsible, cylindrical trees [6], treemaps [53], and Beamtrees [64]. For a more comprehensive overview, see Kosara et al. [28]. In fact, one could argue that the entire field of information visualization is the pursuit of this challenge. Obstacles to overcoming this problem include:

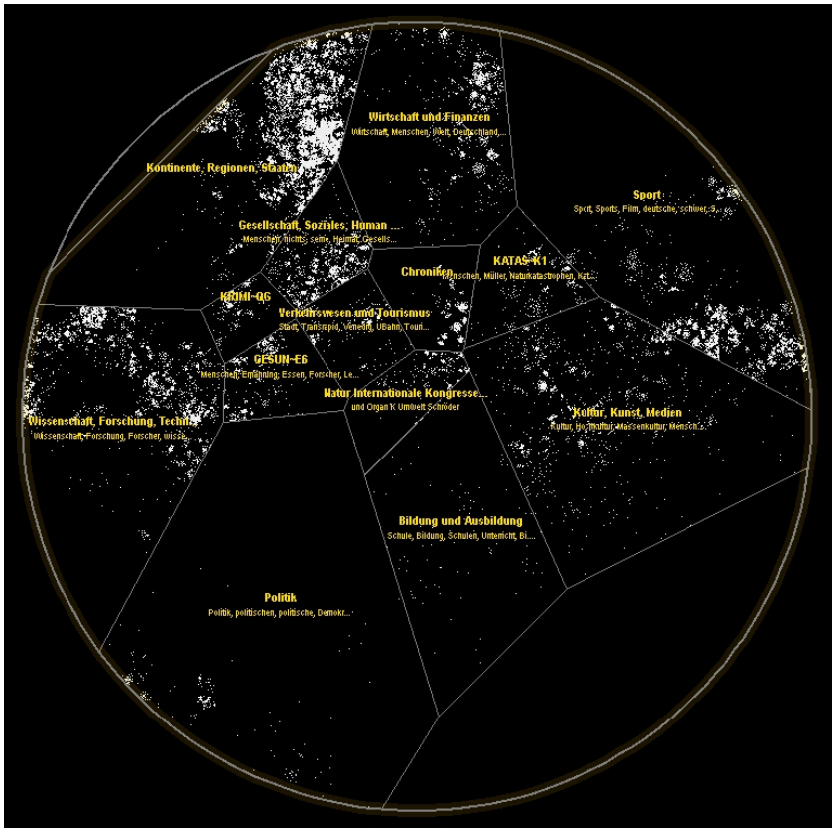

Fig. 1.3. The InfoSky system uses the night sky as a visual metaphor for visualizing large numbers of documents [16]. It was also the subject of a usability study. *Image courtesy of Michael Granitzer et al.*

– *Cognition*: creating visual metaphors that are intuitive from a user-perspective,
– *Scalability*: engineering abstract geometries that can represent large amounts of data,
– *High Dimensionality*: discovering visualizations that are able to encode multi-dimensional data in an intuitive manner.

It is difficult to imagine one visual metaphor that is able to handle all of these aspects. Thus we expect a range of tools and visual metaphors in information applications. One important point to note with this challenge is that the choice of most effective visual metaphors may depend on user expectations and goals.

Challenge #4: Choosing Optimal Levels of Visual Abstraction. This is very closely related to the challenge of finding effective visual metaphors. Bill Hibbard also stressed the importance of defining, "effective abstractions for the visualization and user interaction process" [19]. Thomas and Cook also describe this challenge in Chapter 4–"Data Representations and Transformations" [59]. Essentially, all visualizations that assign a geometry to abstract, non-spatial data are forced to choose some level of abstraction

in order to represent the underlying information. What exactly the optimal level of abstraction is requires serious consideration. Scatter plots are an example of a fine level of abstraction. There is a one-to-one correspondence between data sample and visual representation. However, representing data sets with hundreds of thousands or millions of data samples causes problems with perception and technical difficulties. Many data samples may overlap in image space and using a one-to-one mapping of points to data samples implies that the finest resolution that can represented faithfully is bound to the resolution of the display being used. Raising the level of abstraction to something coarser is required to represent so many data samples effectively. This could be accomplished with a clustering technique for example. Tree data structures are a natural choice for arbitrary levels of abstraction since parent nodes may represent multiple child nodes and trees may contain a more-or-less arbitrary number of levels. However, the higher the level of abstraction, the more difficult cognition and interpretation can be.

One of the central, fundamental challenges implicit with optimal levels of visual abstraction is the fact that "optimal" depends on the user. Some users want a simple, high-level of abstraction with maximal ease-of-use. Other users desire, as-closely-as possible, a direct representation of the underlying data, with as many options as possible for interaction, exploration, and analysis of the data. Implied here is the ability to provide a smooth and intuitive transition between multiple layers of abstraction either with one visual metaphor or with multiple views of the data at different levels of abstraction. Another popular viewpoint is that users follow a general path in the visualization process: (1) start with an overview of the data, (2) select a region of interest, (3) focus on the region of interest by showing more details (overview first, zoom and filter, then details-on-demand [54]). In other words, optimal levels of abstraction must show details on demand. These are tasks that focus+context visualizations address as well as software systems using multiple, linked views [7, 8].

In the end, finding the optimal level of visual abstraction encompasses several other challenges–the solutions to which promise to remain elusive for years to come.

Challenge #5: Collaborative Visualization. This challenge is identified by Hibbard [19] (see challenge number 8 under "Interactions") and discussed again in detail by Thomas and Cook [59], see the topic "Collaborative Visual Analytics". As hardware becomes less expensive, as display technologies advance, and as computing devices become more and more ubiquitous, the demand for collaborative visualization (both co-located and distributed visualization) technology will also increase. The idea is simple, one user investigating some data would like to share their visualization with another user(s)–in a different location. The practice, however, is difficult and full of challenges. If the visualization is static, then the problem reduces to simply sending an image(s) from one location to another–a problem already solved. The future work lies in interaction.

What happens if multiple users in disparate locations would like to explore, analyze, or present their data in an interactive, collaborative manner? There are many related questions that require consideration here:

- *Control*: Who steers the visualization? In other words, who controls the interaction and visualization parameters?
- *Coordination*: How is control passed from one person to another during collaborative visualization? Can multiple users share control simultaneously?

- *Communication*: What is the best way for viewers to communicate observations with each other during synchronized visualization?
- *Network Latency*: What are the bottlenecks introduced by network latency? How can network latency be minimized? What is the best way to handle multiple users, each with different network bandwidth?
- *Display Technology*: Chances are, each user will have different display technology. How can we ensure that each user is actually seeing the same thing?
- *Security*: Should the visualization environment have permissions associated with it? Are some subsets of the visualization private? or public? What is the best way to establish viewing permissions?

Many questions provoked by collaborative visualization suggest a large amount of future research is needed to solve this problem. Protocols need to be engineered that establish coordination during synchronized visualization. In other words, modification of visualization parameters must be done in some coordinated fashion, with pre-established rules. Presumably, each user should be able to speak or at least send messages to each other during the collaboration. What is the best way to establish verbal or written communication with multiple users during the visualization?

Although the speed of networks continues to increased rapidly–it seems it can never be fast enough. And certainly each viewer cannot be expected to have exactly the same network bandwidth. Should the visualization parameters be determined by the lowest common denominator, i.e., the person with the slowest network connection? Users cannot be expected to have the exact same set of hardware, including display technology. The choice of display technology, in theory, should not prevent a user gaining the same insight into the data as the other users. Of course there are many technical issues associated with this that we discuss in another challenge. In fact, the list of open questions is so long that it is almost daunting. Bill Hibbard was also concerned about this topic in 1999 [19]. Thomas and Cook describe this topic again in 2005 as a grand (future) challenge [59]. How much progress have we made in this area since 1999? We refer the reader to Brodlie et al. [3] as well as the chapter on collaborative visualization for a comprehensive overview of distributed and collaborative visualization research.

Challenge #6: Effective Interaction. The challenge of interaction is mentioned several times in related research literature including Hibbard's list, item number 7 under "Interactions" [19], in the future work section of Kosara et al. [28], Johnson's list, item number 6, "HCI" [22], as well as by Van Dam [62, 63]. Two classes of interactions are important here: interaction using the traditional keyboard and mouse and interaction techniques that go beyond the keyboard and mouse.

We mention the first class of interaction techniques because the keyboard and mouse have been around for many, many years now without significant evolution and we believe they are here to stay for many years to come because users are familiar with them. Nonetheless, much work remains in providing *more* interaction to the user of visualization tools and *intuitive* interaction. It seems that no matter how much interaction is provided to the user, the user will always want more with the passage of time and experience. This has been our first-hand experience working in software development alongside mechanical engineers. It is also a theme echoed by many researchers in our field. And with the coming of new visual metaphors come new interaction techniques.

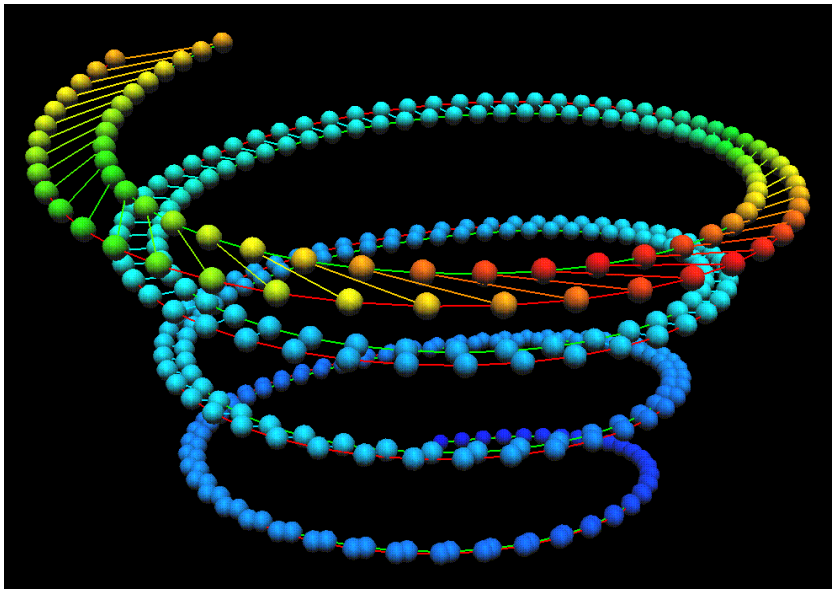

Fig. 1.4. The visualization of uncertainty in fluid flow resulting from different streamline tracing algorithms [39]. Different streamline integration schemes result in different paths, even in the same vector field. *Image courtesy of Alex Pang et al.*

Providing intuitive interaction techniques will be a challenge as long as new visual metaphors are introduced. For example, it is not obvious what the most effective interaction tools are for those wishing to control the visual parameters of a BeamTree [26].

In the other class of interaction, those techniques which reach beyond the keyboard and mouse, developing intuitive interaction techniques is still in the early stages. Direct interaction will be central for users immersed in a virtual world. Much work needs to be done in the areas of voice recognition, gesture recognition, and 3D user interfaces. Clearly, communication with the voice and physical gesture is much more natural and intuitive from a human-centered point of view than using a mouse and keyboard to interact with an arbitrary 2D GUI. Users want to work with their hands as they do in the physical world. Many questions remain to be answered in this growing field. For example, what is the most effective way of drawing a line in 3D?

Challenge #7: Representing Data Quality. This topic comes up often in the visualization community and hence is often cited as a top future challenge [5, 22, 59]. In the scientific visualization literature, this topic is often described using the terms "error" and "uncertainty" visualization [22, 24]. Statisticians may use the term "probability". Information visualization literature may address this theme as assessing the "intrinsic quality" of data [5]. Whatever the term(s) used, there is a common notion being described. Not all data is equal. Data has varying accuracy, reliability, probability of correctness, confidence, or quality.

In scientific visualization, most data sets have an associated measure of error or uncertainty. This error can come from various sources, but it is often associated with

the hardware device that generates the data, e.g., a magnetic resonance imaging (MRI) scanner or some other 3D scanning device. However, this error is only very rarely represented in subsequent visualization [47]. Also in the context of scientific visualization, particle tracing integration algorithms have a certain amount of error associated with them [36], however this uncertainty is normally not represented in the visualization [39] (Figure 1.4). Other examples come from multiresolution (MR) and adaptive resolution (AR) visualization [33]. Each resolution in an MR hierarchy has some measure of error associated with it since a coarser approximation can normally not be as authentic as original, fine resolution data. AR visualizations also normally contain uncertainty in regions of coarser resolution. In both the MR and AR cases, this uncertainty is usually not included in subsequent visualizations.

Other measures of data quality are not difficult to imagine. In an information visualization context, imagine a census collected from two distinct time periods, separated by 10 years. Presumably, the more recent census data is more accurate and thus of higher quality than its older counterpart. Does the newer census data render the old data no longer useful? Not necessarily. The older census may represent a slightly different geographic coverage than the latter. In other words, the physical domain is slightly different for each case. This example brings up two more important factors when considering data quality: namely *temporal factors* and *coverage*. The age of data may influence its quality. More recent data may be considered more reliable. *Incomplete* data is also a problem arising very frequently. In the case of the census data, the more recent census may be considered incomplete if it does not maintain the same geographic coverage of its predecessor.

Erroneous and incomplete data is often discussed in the context of databases. Any database derived from manual data entry is assumed to have both (human) errors and missing items, i.e., incomplete records, sparse fields. And although the data in virtually every database contains some amount of error, this error is more often than not left out in subsequent visualization(s). In fact, so careful are visualization researchers at abstracting away problems with sources of data, that they have developed terms specifically for this purpose: data *smoothing* or sometimes *preprocessing*. We have even heard the term: to *massage* the data (before visualization).

Regardless, the challenge of assessing data quality promises to remain a top unsolved problem for years to come. And we regard this a mainly a human-centered problem. Once an intelligent decision has been made on how to measure or evaluate the quality of a certain data source, we believe technical solutions already exist to incorporate this information into resulting visualizations, e.g., using error bars, standard deviations, confidence intervals, color-coding etc. Essentially any multi-dimensional visualization technique could potentially incorporate this as an additional data dimension.

1.2.2 Technical Challenges

Here we describe the challenges we claim are centered on technical issues like the development of novel, innovative algorithms or challenges closely coupled with hardware.

Challenge #8: Scalability and Large Data Management. A challenge identified by Chen [5] (see problem number 6. “Scalability”), Kosara et al. [28] and Thomas and

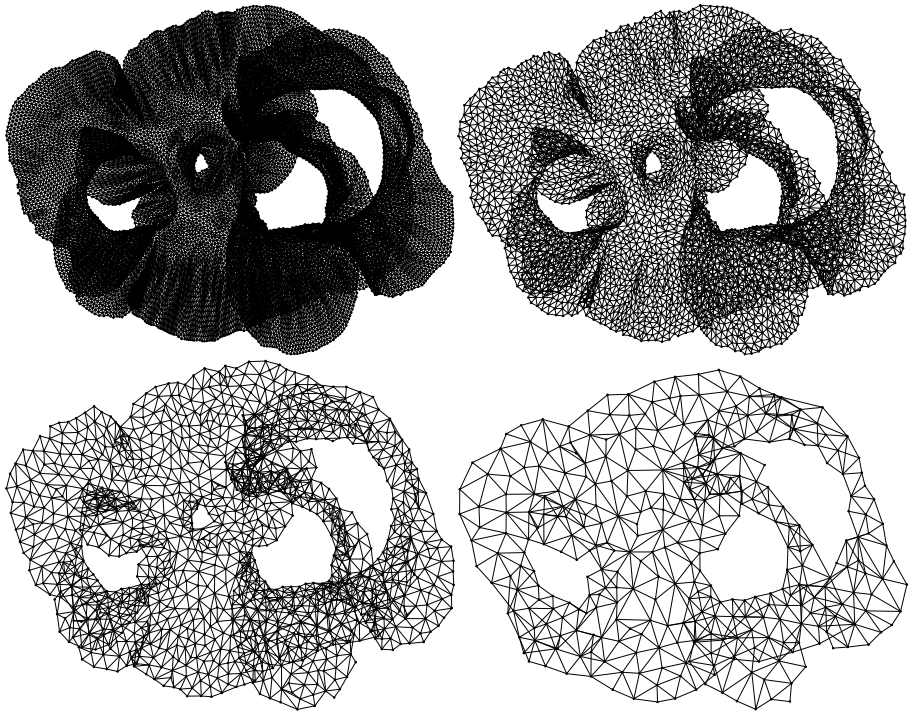

Fig. 1.5. The visualization of a large graph containing 15,606 vertices and 45,878 edges at different scales: (top,left) at the original scale, (top,right) with 4,393 vertices, (bottom,left) with 1,223 vertices, and (bottom,right) with 341 vertices [14]. *Image courtesy of Emden R. Gansner.*

Cook [59], see the topic, "Visual Scalability", most researchers agree that the rate of data growth always exceeds our capacity develop software tools that visualize it. At the very heart of visualization research is the rapid growth of data set sizes and information. The primary motivation for visualization research is to gain insight into large data sets. Software programs are often composed of thousands of files and millions of lines of code. Simulation results are often several gigabytes in size. Databases often store data on the terabyte scale. A popular example of data management on the terabyte scale– generated daily, comes from the field of astrophysics [57]. Very large databases are the focus of their own conferences like VLDB–the annual Very Large Data Base conference, now meeting for over 30 years. Technical problems that form the core challenges are:

– *Designing Scalable Visualizations*: visualization algorithms that are capable of handling very large data sets and scale correspondingly to ever-increasing data sets sizes (Figure 1.5)
– *Limited Processing Speed*: Even with Moore's law describing the growth rate of processing power, software growth seems to exceed the rate of hardware growth.
– *Limited Memory and Storage Space*: visualization technology that makes efficient use of limited storage capacity, e.g. out-of-core algorithms

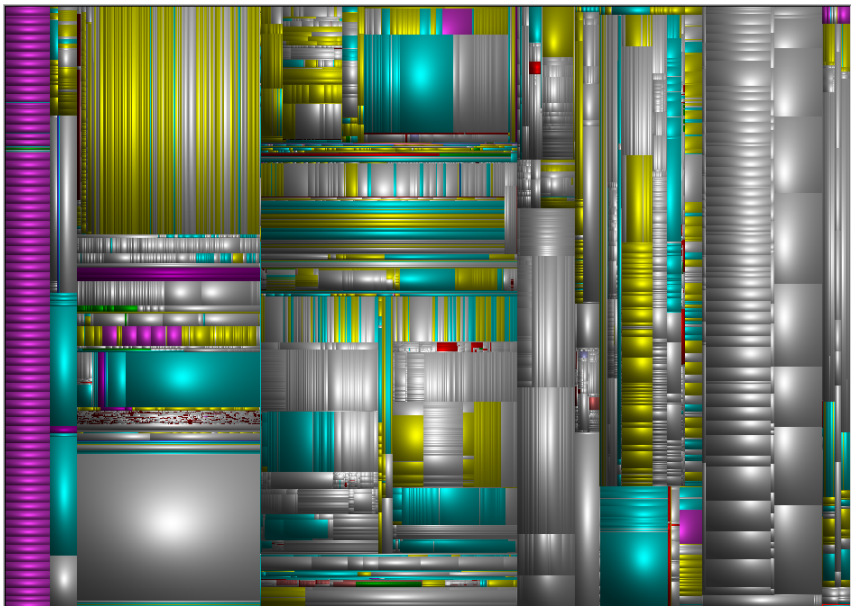

Fig. 1.6. Sequoia View is a very effective tool for visualizing disk space usage [67]. Each file is represented by a rectangle in the image. As of January 2006, it has been downloaded over 500,000 times. *Image courtesy of Jarke J. van Wijk et al.*

– *Limited Network Bandwidth*: visualization algorithms that make efficient use of limited network bandwidth

Scalability and large data visualization were themes in the IEEE InfoVis 2003 Contest. The winner of the InfoVis 2003 contest, TreeJuxtaposer [44], was able to visualize a tree with about 500,000 elements. Clearly, there is still a non-trivial gap between the larger data set sizes and visualization algorithms designed for large data sets. Ideally, visualization algorithms can realize interactive or real-time frame rates. But this is generally not true when data set sizes exceed a certain threshold size. Effective visualization will face the challenge of ever-larger data set sizes and limited processing speed for many years to come.

Note how we have used the term *limited* to describe memory, storage space and network bandwidth. The cost of memory and storage space has dropped dramatically in recent years and availability has increased correspondingly. But the growth of data still exceeds the growth of both memory and storage space and we do not expect this trend to change in the near future. Every practitioner working on a daily basis has had the experience of running out of disk space, e.g., see Figure 1.6. And virtually everyone has gone through the process of finding data to delete in order to free up more space–a task aided by various software programs. In short, data is collected to meet disk storage capacity.

Analogous statements hold true regarding network bandwidth. Network speed has increased rapidly over the last 20 years, but seemingly it can never be fast enough. As

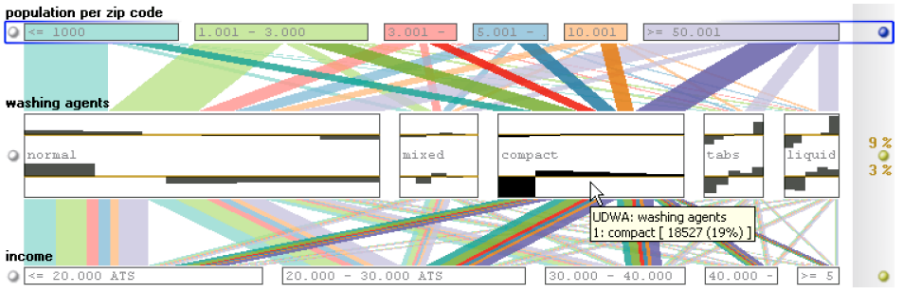

Fig. 1.7. Parallel sets are targeted specifically at the visualization of high-dimensional, abstract data [1]. Parallel sets can be considered an extension of parallel coordinates. This visualization shows the relationships between different questions in the survey. *Image courtesy of Helwig Hauser*.

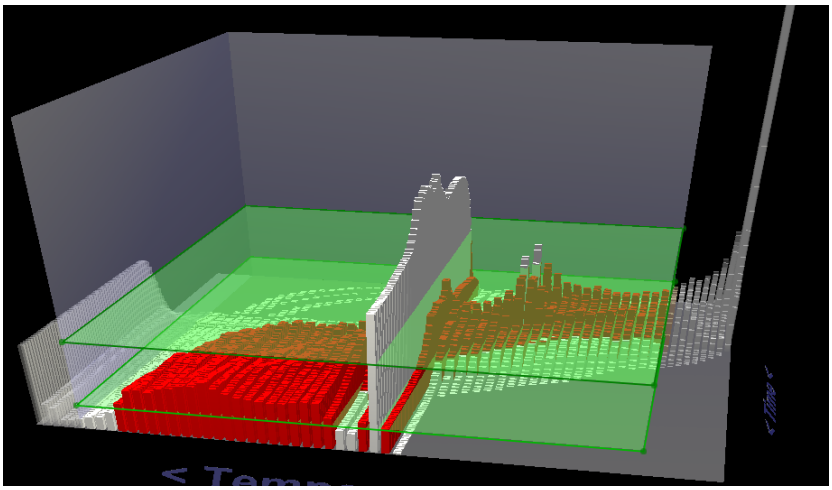

Fig. 1.8. Time Histograms are able to visualize time-dependent data in a still image [27]. Time is given a spatial dimension along one histogram axis.

an example, The VRVis Research Center participated in the IEEE Visualization Contest in 2004, another contest focused at visualizing large data sets. It took two days to download the 60 gigabyte contest data set–the visualization of hurricane Isabel. Furthermore, how many copies of a such data set can be made? Future visualization algorithms must make effective use of both limited storage space and limited network bandwidth if they are to enjoy long term success.

Challenge #9: High Data Dimensionality and Time-Dependent Data. The challenges of high data dimensionality (also called multi-field, multi-attribute, or multivariate data) and time-dependent data are continuous themes throughout the visualization community and appear often in the literature (See Hibbard's challenge number 5

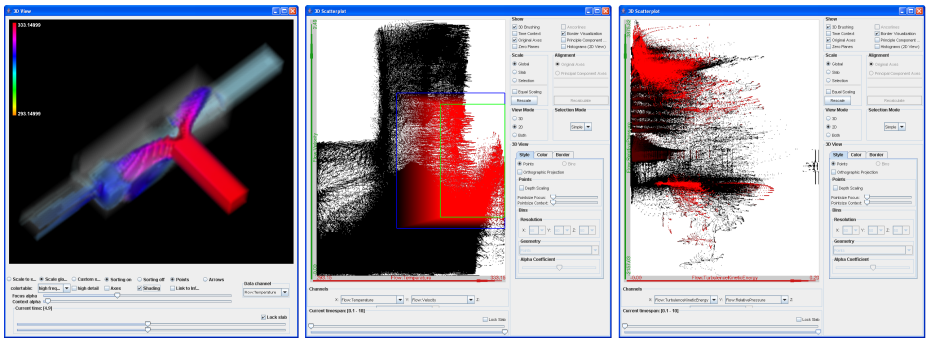

Fig. 1.9. Multiple, linked views are used in combination with brushing (middle) in order to filter out data in areas of interest (left) [9]. On the left is the scientific (or geometric view) of the data while the scatter plot view is on the right. Here CFD simulation data is being analysed. *Image courtesy of Helmut Doleisch et al.*

on information [19] and Johnson's problem number 9 on multi-field visualization [22]).

The VRVis Research Center develops tools to visualize CFD simulation data [32]. Typical CFD simulation data attributes that describe the flow through a geometry include: velocity, temperature, pressure, kinetic energy, dissipation rate, and more. Plus the data sets are time-dependent with possibly hundreds or even thousands of time steps. And this is a description of single phase data. The number of attributes multiplies with each phase in a multi-phase simulation.

With categorical data the problem becomes even worse. If each category is treated as a data dimension, then it's possible to have hundreds of dimensions. An example is described by Bendix et al. [1] who apply parallel sets–an extension of parallel coordinates, to an application with 99 dimensions (Figure 1.7). The case stems from a questionnaire containing information from about 94,000 households attempting to assess living standards. A particularly difficult challenge stems from the objective of trying to understand the relationships between multiple attributes (or dimensions) in the data.

Although time can be considered as another data dimension or attribute, is treated separately here since time normally adds motion to a visualization. Effective, time-dependent visualization techniques promise to remain a future research challenge for several years to come. Watching objects in motion generally provides more insight than static images, but also requires more cognition on behalf of the viewer. The transient nature of a dynamic visualization can make some things not only easier to see, but also more difficult to see, e.g., fast moving phenomena. Also, representing motion in a static image generated from a time varying data set can be very challenging and relatively few methods have been presented on this topic [27] (Figure 1.8). One of the fundamental challenges with representing time in a static image lies in the length of time to be shown–both in the past and in the future. Ultimately, the needs of the user will play a large role in deciding this.

Challenge #10: Data Filtering. As mentioned in our top future research challenge in regards to assessing data quality: not all data is equal. Not only is not all data of equal

quality but not all data is of equal interest or importance. Most would agree that one of the central problems of the current digital age and perhaps even of the twenty first century centers around the fact that we have too much information. In a 2003 study [2] lead by P. Lyman and H.R. Varian entitled "How Much Information", it is estimated that five exabytes (5×10^{18} bytes) of data were produced world wide. And the rate of storage is growing each year at a rate of more than 30%. Consequently, developing tools that filter the data, namely, techniques that separate the data into interesting and uninteresting subsets is one of the major research challenges of the future (Figure 1.9).

As an example, consider the AT&T long-distance telephone network. AT&T maintains a database of all calls made using this network for a time period of one year [23]. The network connects 250 million telephones from which hundreds of millions of calls are made each day. Analyzing and visualizing this data in order to find fraudulent phone calls is a serious undertaking. Developing visualization tools to filter out the important information from such data sets is challenging for at least two reasons. Firstly, the size of the data set makes searching more difficult and time-consuming. Secondly, filtering the data based on importance or interest measures is a function of the user. Different users will filter the data based on different criteria.

In fact, one could view the new field of visual analytics from a pure visual filtering point of view [59]. The goal of visual analytics tools is to separate interesting data from non-interesting data. Visual analytics tools allow users to interactively search data sources for features of interest, special patterns, and unusual activity.

In scientific visualization, such filtering is often called feature extraction [45] or feature detection [22] (challenge number 11) and time-dependent feature extraction is referred to as feature tracking. A typical example of feature extraction can be found in flow visualization. Various algorithms have been developed to extract vortices from vector fields either automatically or semi-automatically. Another approach is to interactively extract features of interest using a combination of multiple, linked information and scientific visualization views [10] (Figure 1.9).

Regardless of the terminology used, software that helps a practitioner search and find those subsets of the data deemed most interesting will be in very high demand in the future. And visualization software is particularly suited for this challenge because it takes advantage of the high bandwidth channel between our visual and cognitive systems.

Challenge #11: Cross-Platform Visualization. This problem is identified multiple times previously [19, 22] and described in detail in Thomas and Cook [59] in the section on "Collaborative Visual Analytics". Two users rarely have the exact same set of hardware. If we consider both the hardware and the software configurations of a user, the probability of an exact match is highly unlikely. For a long time, advances in display technology were fairly slow. However, flat panel display technology has made rapid advances in recent years. The cost of display technology has also fallen, making display technology virtually ubiquitous in many countries. If we consider the range of possible hardware configurations: from desktops and laptop computers with various combinations of graphic cards and monitors, to handheld devices like cell phones, PDAs, and

[2] Available at:
`http://www.sims.berkely.edu/how-much-info`

other electronic hand-held devices, to large displays using digital projectors, and we throw in various operating systems and memory resources for each of those devices then we are left with a vast array of possible hardware and software combinations. And the range of different possibilities is expanding, yet each user will demand advanced visualization functionality. Consequently, visualization tools that are able to cross inter-platform bridges will remain a serious challenge in the future just from a technical point of view (and also from a human-centered point of view as mentioned in the challenge concerning collaborative visualization).

Currently we are witnessing an explosion in research literature related to the topic of programmable graphic card capabilities [11]. Many visualization algorithms have been written that are tied to an individual graphics card and the set of programming language capabilities that it supports. We see a rather negative aspect of this trend and we are not in full support of this as a research direction. In fact, this trend works against the goal of cross-platform visualization. Have you ever asked a practitioner, e.g., an engineer, what kind of graphics card their workstation has? Tying an application to a specific graphics card has some negative implications: one of which is a sharp increase in cost. Imagine requiring specific hardware and application software to be sold together. That would imply that a user would have to buy a special workstation just for one visualization application. The scenario quickly becomes infeasible if we ask a user to buy a separate set of hardware for each software application. It is rather the job of the operating system software to be tied to the hardware and not necessarily the application software. The exception to this is when cross-platform standards, like OpenGL, are introduced–another future research challenge found on our list.

1.2.3 Financial Challenges

Here we separate out literature on the topic of financial challenges facing visualization researchers. Seldom are financial challenges address explicitly in related literature. Financial challenges certainly abound however. This is especially true when one equates investments of time with money–something reasonable since time is costly. Note that this group of related work and challenges could also be re-formulated under the theme of transforming research into practice.

Challenge #12: Evaluating Effectiveness and Utility in Practice. Also identified as a future problem by Chen [5] (see unsolved problem number 5 “Intrinsic quality measures), human-centered evaluation of visualization software is a common and old theme. Evaluation of visualization tools from an economic standpoint is a relatively new topic. Nonetheless it is very important. Are all research directions of equal worth? Probably not. Can all research directions be pursued? Again, this is most unlikely. Certainly, problems that are considered by many to be solved, like volume rendering of medical data [40], deserve less attention than unsolved problems. We also consider the problem of 2D flow visualization, both steady and unsteady, to be solved [65]. How do we as researchers decide where to invest our time and money?

Jarke van Wijk presents, to our knowledge, the first attempt at assessing the value of visualization from a practical and economic standpoint [66]. A model is presented

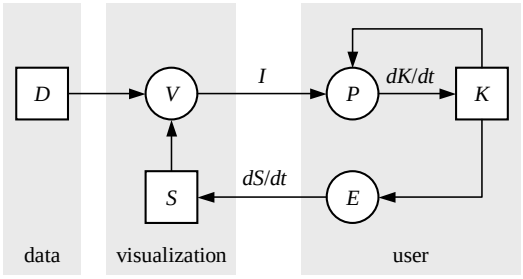

Fig. 1.10. A simple model to assess the value of a visualization [66]. D = data, V = visualization, I = image, P = perception, K = knowledge, S = specification, E = exploration. *Image courtesy of Jarke J. van Wijk.*

that summarizes the requirements and processes associated with creating and evaluating visualization software (Figure 1.10). Several cost factors are identified. From an economic point of view, costs include:

- An initial development cost: This includes one or more software engineers and may include the acquisition of new hardware.
- An initial cost per user: The user must learn how to generate a visualization result using the developed software. In the CFD community, this process may take weeks, even months since simulation result may take a long time to compute and CFD software can be complex and feature-rich.
- Costs per session/use: This includes the time it takes the user to generate the required visualization from a given algorithm or method each time of use.
- The cost of cognition: This is the time the user needs to understand and explore the visualization result and thus gaining knowledge or insight into the underlying phenomenon.

The costs identified in this list must be multiplied by the number of developers and users respectively. In short, the cost of development and use is expensive. The take away? Careful consideration is required if we would like to invest our time and money properly.

Can visualization survive without customer demand? This was an important question raised by Bill Lorensen [40]. Lorensen argues that the success of research in computer graphics owes to the fact that there is a large customer demand–the computer gaming industry. In order to succeed the visualization community must establish better contact with potential customers–a challenge discussed here previously. Part of this must include the assessment of value. We must be able to offer something of value to potential practitioners. In order to do this, we need a way to assess value of visualization from an economic standpoint. This promises to remain a central challenge for visualization researchers for the foreseeable future.

Challenge #13: Introducing Standards and Benchmarks. Other areas of computer science have developed standards and benchmarks. Databases have standard normal forms. Networking is full of standard protocols. Many standard sorting algorithms are

used. Standards represent progress in the field and are important to future, widespread use and success. Visualization lacks standards and benchmarks. (See also Thomas and Cook [59]) This encompasses several different aspects:

- *Standard Data File Formats:* The field of visualization is lacking standard data file formats. In CFD alone, several different data file formats exist. In medical visualization, much work has been done in order to establish a standard file format [55]. In information visualization, perhaps the closest thing to a standard file format is XML.

- *Standard Visualizations:* The closest thing we have now to standard visualizations are pie charts, bar graphs, and 2D scatter plots. However, these are already quite old, generally restricted to 2D, and are generally not interactive.
- *Standard Interaction Techniques:* Scaling (or zooming), rotation, and translation (or panning) are simple, standard interactions in a visualization application. However, from a users perspective their use is certainly not standard. Each application has its own way of rotating an object.
- *Standard Interfaces:* Standard interfaces, like OpenGL, are a great contribution to the field. Continued development of such interfaces is very important in order to enable cross-application interaction.
- *Standard Benchmarks:* Benchmark tests and data sets are used in industry before a software release. Standard benchmarks, including standard data sets, could also be used to demonstrate and compare new algorithms to their predecessors.

Lacking standard data file formats makes the problems of sharing data and comparing algorithms more difficult. It also generates more work thus slowing progress. One of the major problems is finding the proper trade-off between usability and compactness for large data sets. Identifying standard, up-to-date visualizations which have proven to be effective would help in comparing and evaluating novel visualizations. Trying to identify both standard visualizations and standard interaction techniques is difficult because of the large variety that have been introduced by the research community. Volume rendering with typical transfer functions like maximum intensity projection is established enough now that perhaps that could be considered a standard visualization. Panning, rotation and zooming are standard interaction techniques but each application has its own set of additional interaction capabilities.

Standard hardware and software interfaces are the key to system interoperability. System interoperability is one of the grand challenges identified by Thomas and Cook [59]. Teams will be deployed to develop disparate applications in disparate locations, yet interoperability standards must be developed if different groups are to work together and benefit from one another's implementation work.

We consider establishing benchmarks mainly as a financial challenge because of the financial and temporal investments that must be carried out for success. For example, who is willing to pay for a web server that hosts a collection of large data sets? Who is willing to invest the time it takes to maintain a web site or other hardware and web pages that describe and distribute standard, benchmark data sets? The importance of standard benchmarks and data sets is now fully recognized by the visualization community with the introduction of the IEEE InfoVis and IEEE Visualization contests. The motivation behind these contests is to introduce community-wide availability to challenging data

sets that can be used to test any visualization technique. Further development of standards and benchmarks will certainly remain a financial challenge for a long time to come because developing such standards requires a long-term investment of time and labor.

Challenge #14: From Research Into Practice. As mentioned previously, visualization research is not for visualization's sake itself just as research in general is not for research's sake. The long term goal of research is to make a useful and important contribution to society at large. Transforming research ideas and prototypes into real applications will play a central role if we are to make a contribution to society as a whole. This challenge also pervades the visualization community. It's discussed by Thomas and Cook [59] (See the chapter entitled, "Moving Research into Practice".) and was the topic of multiple, recent, discussion panels [51, 58]. We save this future challenge for last because it encompasses so many other challenges described previously:

- *Interdisciplinary Communication*: Turning research into practice will require collaboration with professionals from other disciplines (Section 1.2.1).
- *Evaluation of Usability*: Building software that supports a wider user audience (Section 1.2.1).
- *Scalability and Large Data Management*: Building software that is supports a wide variety of real-world, multi-scale, possibly incomplete or sparse data sets (Section 1.2.2).
- *Cross-Platform Visualization*: Deploying applications that run on more than one software and hardware platform (Section 1.2.2).

Another area key to the success of bringing research into practice includes educating users. That means more pedagogic literature needs to be published. Bringing knowledge to public both written and verbally will play a vital role.

We consider this mainly a financial challenge because the knowledge necessary for building an industry-grade software product is already available. The main question is finding the required man-power, e.g., the time and money necessary to build a real-world software application. Considerable progress has already been made in this area. Many commercial applications have been built using the VTK [52]. Advantage Windows from GE and Vitrea from Vital Images are also examples of successful visualization applications used in industry [40]. However, visualization applications are still not generally known as success stories. The gap between researchers and the needs of application scientists is well known. Bringing more research prototypes into the hands of real users will remain a challenge for the foreseeable future.

1.3 Discussion, Comments on the Future, and Conclusions

We have presented a literature survey of selected future challenges and unsolved research problems in visualization, with an emphasis on human-centered aspects. We note that our survey did not cover every single topic mentioned in the literature, but concentrated on those themes that were mentioned in multiple sources and where some (at least minimal) level of consensus was reached. Some of the unsolved problems and future challenges that we did not list specifically include:

- **Improving Visual Quality:** Producing hardware displays which are indistinguishable from physical reality (see challenge number 1 on Visual Quality from Hibbard [19]).
- **Integrating Virtual with Physical Reality:** Solving this problem would involve eliminating head mounted displays, special gloves or glasses, and embedding displays directly into the physical environment (see challenge number 2 on Visual Quality from Hibbard [19]).
- **Integrating Problem Solving Environments:** This is also sometimes referred to as computational steering and means allowing the user to interactively steer a computation in progress (see challenge number 8, "Integrated Problem Solving Environments (PSEs)" from Johnson [22]).
- **Developing a Theory of Visualization:** Some researchers feel that visualization as a discipline does not contain enough fundamental theory on which the premise itself (see challenge number 15, "Theory of Visualization" from Johnson [22]).
- ***A Priori* Knowledge:** Building visualization tools that take into account the already existing amount of application domain knowledge the user may have. (see challenge number 3. "Prior Knowledge" of Chen [5]).
- **Improving Aesthetics:** Improving the resulting appearance of a visualization is an important future problem identified by Chen [5] (see challenge number 7. "Aesthetics" [5]).
- **Privacy and Security:** Producing software which is capable of data anonymization, audit trails, and access controls to protect privacy or provide information security is a grand challenge identified by Thomas and Cook [59] (see Chapter 6, "Moving Research into Practice").
- **Reducing Complexity:** Although this problem is not stated and described explicitly in the related literature, we feel that tools and techniques that focus on reducing complexity, especially from an implementation point of view, will be important and pose a difficult challenge to future visualization researchers.

Concerning the future of future challenges and unsolved problems in human-centered visualization, an outlook is difficult to predict. Perhaps 20 years from now the visualization community will again go through a similar phase of evaluation, self-criticism, and retrospection–seeking new directions. What brand new problems researchers will face is intriguing. We can, with caution and some margin of error, however, guess what problems here might be solved 20 years from now:

Solved Challenges in 20 Years.

- *Interdisciplinary Collaboration*: We think this is a solvable problem within (less than) the next 20 years.
- *Finding Effective Visual Metaphors*: This problem also has the potential to be solved before the next phase shift.
- *Representing Data Quality*: We are optimistic and believe this will fall under the list of solved problems.
- *Transforming Research Into Practice*: The knowledge necessary to solve this problem already exists.

(Still) Unsolved Challenges in 20 Years.

- *Evaluation of Usability*: Research in this area is still in the early stages. We think it will be only partially solved in 20 years.
- *Choosing Optimal Levels of Abstraction*: This problem is complex enough that we think it will still require more work in 20 years.
- *Collaborative Visualization*: The complexity here combined with the lack of progress in the last five years makes us confident that this problem will still remain unsolved in 20 years.
- *Effective Interaction*: We expect effective interaction to be solved in the traditional desktop environment, but not in environments beyond the desktop, e.g., virtual reality environments.
- *Scalability and Large Data Management*: This problem has been around for more than 20 years. Maybe this problem will be even worse in 20 years.
- *High Data Dimensionality and Time-Dependent Data*: This one is difficult to predict. We error on the side of caution and categorize it as unsolved in 20 years.
- *Data Filtering*: Again, the complexity here combined with the ever-expanding data set sizes leads us to believe that this problem will not be solved by then.
- *Platform Independent Visualization*: Will remain unsolved.
- *Evaluating Effectiveness and Utility*: It is not clear that this problem can ever be solved given its subjective nature.
- *Introducing Standards and Benchmarks*: We predict that this will be a partially solved problem in 20 years.

The list of solved problems is shorter than the list of unsolved problems. However, the list of unsolved problems contains partially solved challenges.

We recognize the subjective nature of the topic and realize that no such list will appeal entirely to all readers. Hopefully our description will provide readers with a starting point and overview of both solved and unsolved problems in visualization. We also aim at sparking thought provoking discussion. We trust the reader will conclude that many unsolved problems and thus much future research remains. Correspondence is solicited. To contribute feedback to this survey of future challenges and unsolved problems in visualization research, please contact Robert S. Laramee [3].

[3] The authors thank all those who have supported to this work including AVL (www.avl.com) and the Austrian research program Kplus (www.kplus.at). The first author may be contacted at: r.s.laramee@swansea.ac.uk.

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Index