Painting and Visualization

Robert M. Kirby
School of Computing and
Scientific Computing and Imaging Institute
University of Utah

Daniel F. Keefe and David H. Laidlaw
Visualization Research Laboratory
Department of Computer Science
Brown University

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1 Introduction

Art, in particular painting, has had clear impacts on the style, techniques, and processes of scientific visualization. Artists strive to create visual forms and ideas that are evocative and convey meaning or tell a story. Over time, painters and other artists have developed sophisticated techniques, as well as a finely tuned aesthetic sense, to help accomplish their goals. As visualization researchers, we can learn from this body of work to improve our own visual representations. We can study artistic examples to learn what art works and what does not, we can study the visual design process to learn how to design better visualization artifacts, and we can study the pedagogy for training new designers and artists so we can better train visualization experts and better evaluate visualizations. The synergy between art and scientific visualization, whether manifested in collaborative teams, new painting-inspired visualization techniques, or new visualization methodologies, holds great potential for the advancement of scientific visualization and discovery.

Scientific visualization applications can be loosely divided into two categories: expository and exploratory. In this chapter, we will focus on exploratory applications. Exploratory applications typically represent complicated scientific data as fully as possible so that a scientific user can interactively explore it. Per the scientific method, a scientist gathers data to test a hypothesis, but the binary answer to that test is usually just a beginning (see Fig. 1). From the data come ideas for the next hypothesis, insights about the scientific area of study, and predictive models upon which further scientific advances can be made. Exploration of increasingly complicated and inter-related data become a means to that end.

One of the most complicated types data that scientists wish to explore and understand comes in the form of multivalued, multidimensional fields. There are a number of visualization application areas that work with this type of data, including fluid dynamics and medicine. These data are difficult to understand because so many variables, or values, are of interest to the scientists. The challenge comes in understanding the correlations and dependencies between all of the values. For example, 2D fluid flow simulations produce a 2D vector field that is sometimes time-varying. From this field, additional scalar, vector, and tensor fields are often derived, each relating to the others and providing a different view of the whole. Displaying such multivalued data all together is difficult, even in 2D. It requires showing six to ten different values within a single image. For 3D fluid flow, the data exist within a volume. Representing a 3D vector field alone is a challenge; representing such a vector field together with derived scalar, vector, and tensor fields is an extremely difficult problem in visual representation.

We will begin with a narrative of some of our work in the area of representing multivalued data, illustrating more specifically some of the ways in which art can be brought to bear on scientific visualization. We will then give a broader survey of scientific visualization work that has been influenced by art, followed

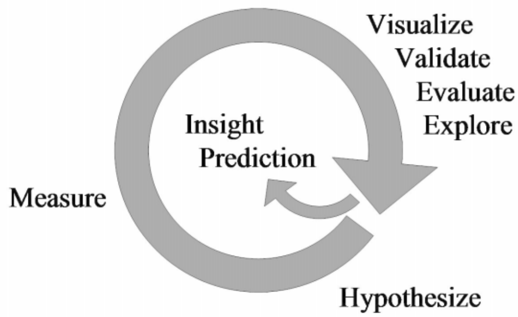

Figure 1: Exploratory scientific visualization is a specific instance of the scientific method. It begins with a hypothesis about some physical phenomenon. It continues with the collection of data that is expected to validate the model. Visualization of the data then helps in the validation of the hypothesis and in generating new hypotheses and insights, often iteratively.

by a discussion of some of the open issues in this area, which will tie back to studying art, design, and art education.

2 Mimicking Artists: Strokes, Design, Critiques, and Sketching

Perhaps the most compelling reasons for visualization researchers to look toward oil painting, and to art in general, are the visual richness and visual effectiveness of the art that we see in our everyday lives. Paintings and reproductions are accessible in museums, posters, calendars, and on the web because there is a demand for them – they are broadly appealing and often convey a meaning or narrative to which we can relate.

Besides their obvious visual appeal, we can learn from art, artists, and art teachers what is visually compelling, what works for specific visual goals, how to tell if something is working, the process of visual design, and the process of learning visual design. Over the last several years we have been exploring each of these areas and will try to illustrate some of what we have learned with examples from those efforts.

2.1 Strokes

Some of our earliest attempts to borrow ideas from the art world began with trips to museums to view paintings and loosely emulate the techniques that we saw there. We were expertly accompanied by artist davidkremers, who guided us through the collections, showing us what he felt would be most relevant to our scientific visualization process. We absorbed ideas, transformed them to our digital medium, and generated a series of visual representations of multivalued data.

This stage was motivated by Meier's work to create painterly animations [25]. Her haystack image (see Fig. 2) illustrates how brush strokes can be layered to build up a compelling visual image. This same layering process is common in oil painting, although deconstructing it is more difficult.

In our early examples we used software that created data-driven visualization by layering "strokes" onto a 2D "canvas." Many visual characteristics of the strokes were set directly from the data, with the mapping under the control of the user. The images are data driven but are not guided by a particular scientific problem; they are experimentation with a new medium. Some of our experiments involved varying stroke

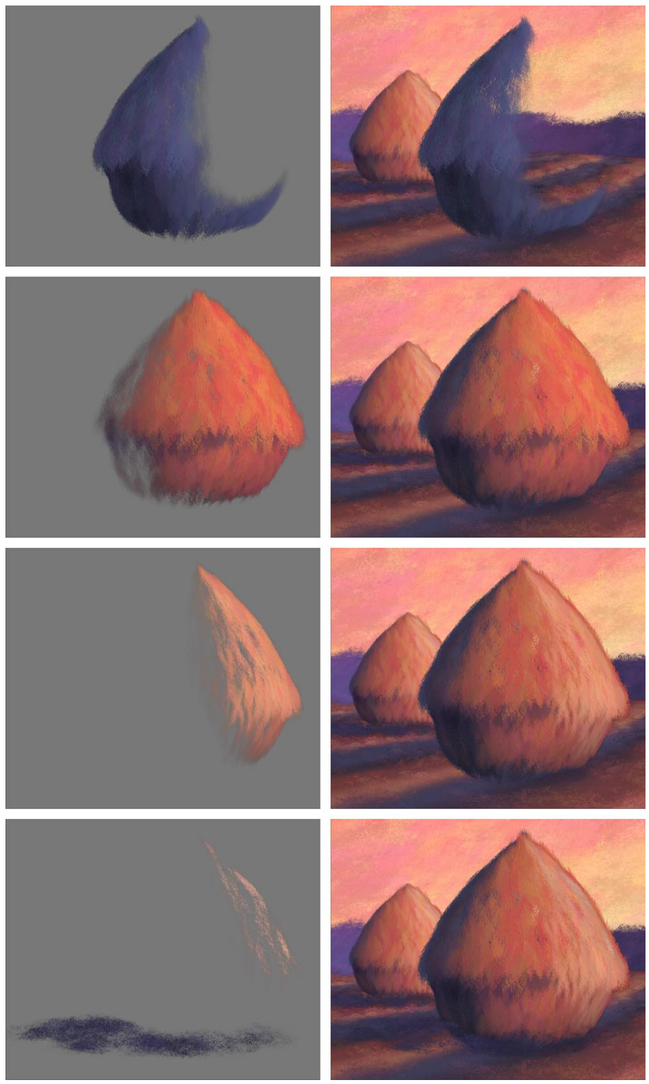

Figure 2: Meier layered strokes to build up computer paintings much as painters layer their strokes to build up an oil painting. The stroke layers are shown here as they accrete. Here, the layers are organized around form and lighting, but other organizing principles can work in other contexts.

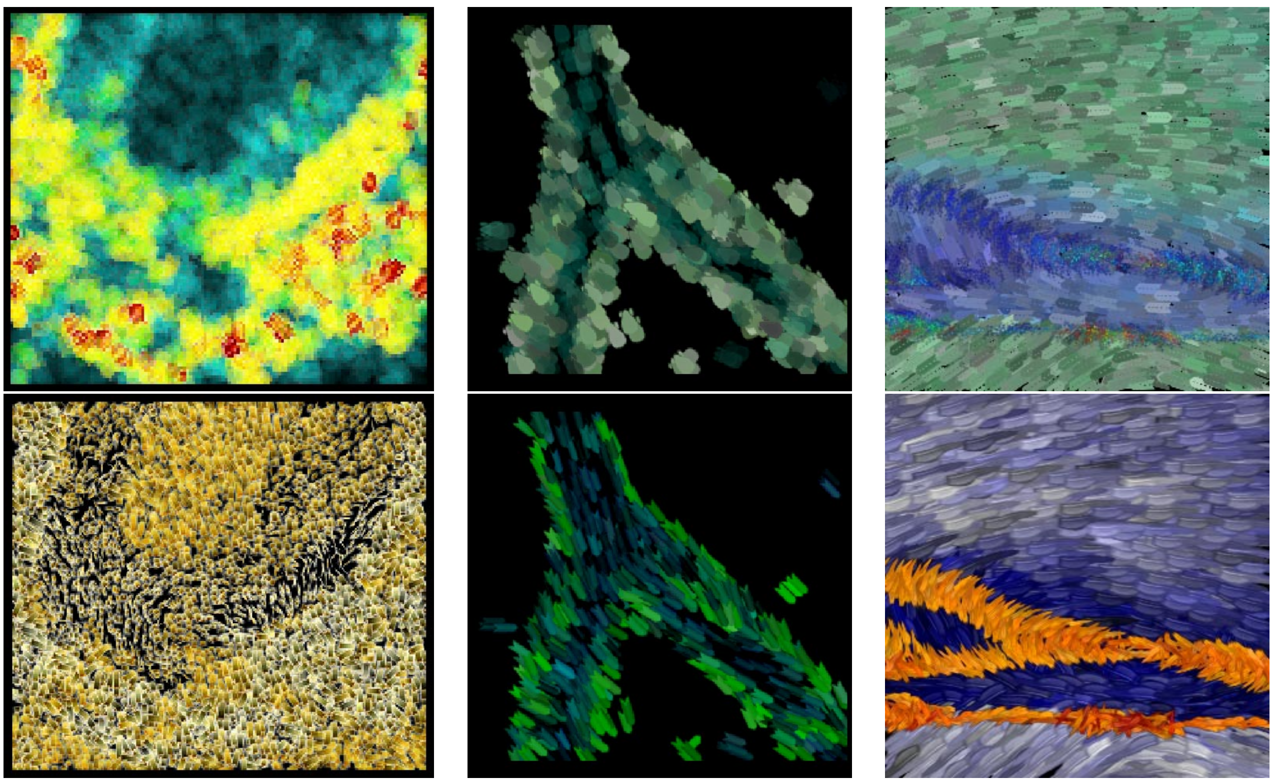

Figure 3: Several early "painterly" visualizations. We experimented with varying the visual representation of underlying data by changing stroke shapes, texture, color, size, and placement. The top and bottom image in each pair are the same underlying data.

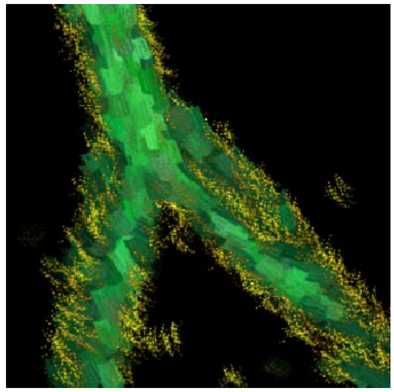

Figure 4: Scumbling, or lightly painting over an already-painted region, is an example of a painting technique we mimicked. We used small strokes to emulate the small bits of paint left behind.

shape, texture, color, and size; changing relationships among layers; and modifying the placement of strokes. Fig. 3 shows some examples.

In one example of a technique we worked to mimic, a painter uses a lightly loaded brush to paint over a dry, but previously painted, region. The texture of the underlying dry paint catches wet paint off the brush, leaving small textured bits of paint. Our version, shown in Fig. 4, used small strokes in a layer atop much larger ones, placed in only a small portion of the image, and in a contrasting color.

From this work we sensed potential. Some of the images created are visually compelling, and the sources of inspiration seem only touched upon. We were also excited by the potential to incorporate time into visualization design. By mapping some parts of data to quickly-seen visual cues and others to visual cues that are seen less quickly, the order in which data is seen in a visualization may be controlled.

This early work also reminded us that there was no evidence that these images would have scientific value. While they were data driven in the sense that data values controlled many of the visual attributes in the images, they were not targeted at solving a specific scientific problem. Indeed, measuring the effectiveness of visualization methods is a controversial and difficult problem.

It also pointed out to us that design decisions sometimes have unintended consequences. For example, some of the painterly experiments had a sense of depth from regions that were lighter or darker. Qualities like this can be difficult for an untrained eye to notice but can dramatically effect our perception of a scene or data.

2.2 Designing Scientific Visualizations

As a follow-on to our early experimentation, we created a set of visualizations addressing three scientific applications using multivalued 2D imaging data: sections of 3D tensor-valued MR images [19], 2D fluid flow (and derived quantities) [16], and six-valued multi-echo MR images [22]. We will discuss in this section the painting-related motivation behind the 2D flow application and also try to provide some insight into the issues with which we grappled.

In [16] we examined the scientific problem of understanding fluid flowing past a cylinder. The primary focus of the study was to visualize multivalued data. Within the study of fluid mechanics, many mathematical constructs are used to enhance our understanding of physical phenomena. Visualization techniques are often used as tools for developing physical intuition of these quantities. One important question, however, is: What do we visualize? To maximize their potential to cross correlate information, scientists usually want to maximize the amount of comprehensible data presented in one visualization. For example, scientists often choose to examine derived quantities, such as vorticity, along with standard quantities such as, velocity and

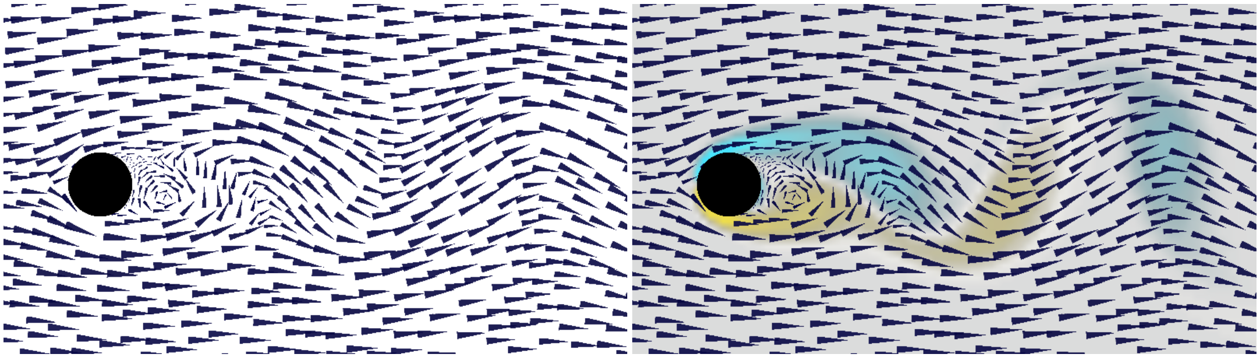

Figure 5: Typical visualization methods for 2D flow past a cylinder at Reynolds number 100. On the left, we show only the velocity field. On the right, we simultaneously show velocity and vorticity. Vorticity represents the rotational component of the flow. Clockwise vorticity is blue, counterclockwise yellow.

pressure, in an effort to fully understand the underlying process of fluid flow.

We illustrate the complexity of this issue by displaying velocity and vorticity simultaneously (see Fig. 5). Vorticity is a classic example of a mathematical construct that provides information not immediately apparent in the velocity field. When examining only the velocity field, it is difficult to see that there is a rotational component of the flow in the far wake region of the cylinder (to the right). But, when vorticity is combined with the velocity field, the underlying dynamics of vortex generation and advection is more apparent.

Although vorticity cannot be measured directly, its relevance to fluid flow was recognized as early as 1858 with Helmholtz's pioneering work. Vorticity as a physical concept is not intuitive to all, yet visualizations of experiments demonstrate its usefulness, and hence account for its popularity. Vorticity is derived from velocity, and *vice versa* under certain constraints[27]. A function and its derivative are similarly related. Hence, vorticity does not provide any new information that is not already available from the velocity field, but it does emphasize the rotational component of the flow. The latter is clearly demonstrated in Figure 5, where the rotational component is not apparent when one merely views the velocity.

Other derived quantities, such as the rate of strain tensor, the turbulent charge and the turbulent current, can be of value in the same way as vorticity. Since examination of the rate of strain tensor, the turbulent charge, and the turbulent current within the fluids community is relatively new, few people have ever seen visualizations of these quantities in well known fluid mechanics problems. Simultaneous display of the velocity and the quantities derived from it is done both to allow the fluids' researcher to examine these new quantities against the canvas of previously examined and understood quantities, and also to allow the fluids' researcher to accelerate his understanding of these new quantities by visually correlating them with well known fluid phenomena.

In our painting inspired visualizations of fluid flow, we sought representations inspired by the brush strokes artists apply in layers to create an oil painting. We copied the idea of using a primed canvas or underpainting that shows through the layers of strokes. Rules borrowed from art guided our choice of colors, texture, visual elements, composition, and focus to represent data components. These ideas are discussed in more depth in [18, 19].

In one of our visual designs, shown in Fig. 6 (left), we wanted the viewer to first read velocity from the visualization, then vorticity and its relationship to velocity. Because of the complexity of the second-order rate of strain tensor we want it to be read last. We describe the layers here from bottom up, beginning with a primed canvas, adding an underpainting, representing the tensor values transparently over that and finishing with a very dark, high-contrast representation of the velocity vectors.

• **Primer** The bottom layer of the visualization is light gray, selected because it would show through the transparent layers to be placed on top.

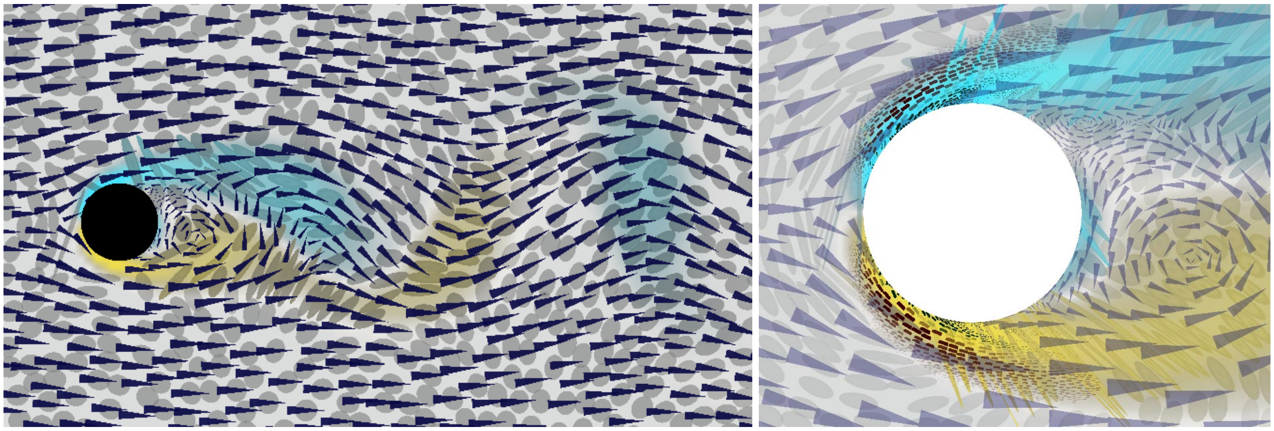

Figure 6: Left: Visualization of 2D flow. Velocity, vorticity, and rate of strain (including divergence and shear) are all encoded in image layers. Right: Additional values turbulent charge and turbulent current for Reynolds number 100 flow are added to the visualization. A total of nine values are simultaneously displayed.

• **Underpainting** The next layer encodes the scalar vorticity value in semi-transparent color. Since the vorticity is an important part of fluid behavior, we emphasized it by mapping it onto three visual cues: color, ellipse opacity, and ellipse texture contrast (see below). Clockwise vorticity is blue and counter-clockwise vorticity yellow. The layer is almost transparent where the vorticity is zero, but reaches 75% opacity for the largest magnitudes, emphasizing regions where the vorticity is non-zero.

• **Ellipse layer** This layer shows the rate of strain tensor and also gives additional emphasis to the vorticity. The logarithms of the rates of strain in each direction scale the radii of a circular brush shape to match the shape that a small circular region would have after being deformed. The principal deformation direction was mapped to the direction of the stroke to orient the ellipse. The strokes are placed to cover the image densely, but with minimal overlap. The color and transparency of the ellipses are taken from the underpainting, so they blend well and are visible primarily where the vorticity magnitude is large. Finally, a texture whose contrast is weighted by the vorticity magnitude gives the ellipses a visual impression of spinning where the vorticity is larger.

• **Arrow layer** The arrow layer represents the velocity field measurements: the arrows point in the direction of the velocity, and the brush area is proportional to the speed. We chose a dark blue that contrasts with the light underpainting and ellipses, so that the velocities would be read first. The arrows are spaced so that strokes overlap end-to-end but are well separated side-to-side. This draws the eye along the flow.

• **Mask layer** The final layer is a white mask covering the image where the cylinder was located.

In a second visual design, shown in Fig. 6 (right), we added two additional derived flow quantities, turbulent current, a vector, and turbulent charge, a scalar. The layers from the first design were changed to make the ellipses and arrows less contrasting and an additional layer added atop them:

• **Turbulent sources layer** In this layer we encode both the turbulent charge and the turbulent current. The current is encoded in the size and orientation of the vector value just as the velocity in the arrow layer. The charge is mapped to the color of the strokes. Green strokes represent negative charge and red strokes positive. The magnitude of the charge is mapped to opacity. Where the charge is large, we get dark, opaque, high-contrast strokes that strongly assert their presence. Where the charge is small, the strokes disappear and do not clutter the image. For these quantities, that tend to lie near surfaces, this representation makes very efficient use of visual bandwidth. The strokes in this layer are much smaller than the the strokes in the arrow layer. This allows for finer detail to be represented for the turbulent sources, which tend to be more localized. It also helps the turbulent sources layer to be more easily distinguished from the arrows layer than in the previous visualization, where the stroke sizes were closer and, therefore, harder to disambiguate visually.

The use of these painting and design concepts helped us create a visual representation for the data that encoded all of the data for a more holistic understanding. The images in this 2D flow example, and in the other application areas described elsewhere, simultaneously display six to nine data values while qualitatively representing the underlying phenomena, emphasizing different data values to different degrees, and displaying different portions of the data from different viewing distances. These qualities lead a viewer through the temporal cognitive process of understanding interrelationships in the data much as a painting can lead a viewer through the visual narrative designed by the painter.

We were left with several observations and questions from this work. First, the images became more iconic than our early experiments as they were targeted at specific scientific applications. They have a less painterly look, as a result.

Also, once again, the question arises, how can we evaluate visualizations? User studies are a stock visualization answer, but we also wondered if we could borrow from art and art education in evaluating visualizations.

2.3 Art Education

Perhaps the most important educational tool to the art instructor is the critique, or crit, for short. Art critiques can take on many different forms, but in a typical classroom, group-critique setting, they often involve displaying the work of all the students and then moving from piece to piece discussing and dissecting the visual decisions and techniques employed. The instructor running the critique usually has very specific goals in mind for the process and leads the discussion and criticism in a direction that culminates in the transmission of some design concept or theory to the students.

Critiques are a checkpoint along a path to creating visually refined imagery. They are almost always a part of a larger, iterative process. The lessons learned in a critique should carry on to future work, either in the form of a refinement of an initial design based on feedback, or as a lesson applied to a completely new design in the future. A critique that doesn't lead to new thought or work by the student is a failure.

Our initial experience applying the concept of critiques to visualization problems is encouraging. The critique framework, especially when expert artistic illustrators, designers, and instructors are involved, may offer an excellent alternative or complimentary approach to the traditional user studies used to evaluate visualizations.

Some of our experience with this framework came in the form of a class we taught in conjunction with Fritz Drury, head of the Illustration department at the Rhode Island School of Design (RISD). The class was composed of half RISD students and half Brown University students. Our focus for a semester was to learn how to visually represent time-varying 3D fluid flow data generated computationally. We started our exploration of visual representation with 2D fluid flow problems, and eventually created visualizations of 3D flow that run in a Cave virtual reality display. Throughout the process, students worked on weekly design assignments, and each week these were expertly critiqued to teach how to create successful designs from both visual and scientific standpoints. The importance of enabling a scientist to perform a specific task, such as locate areas of high vorticity within a flow, was a new constraint for RISD design students. The depth of understanding reached by the class on the effects of color, texture, form, and iconic representation upon human perception, particularly in virtual reality, was new territory for all the students.

Some results from a 2D flow visualization design assignment are shown in Fig. 7. Input from the critique of these works helped shape the students' future assignments as well as the final class projects in virtual reality. Based on feedback in weekly critiques, most designs in the class were eventually refined to the point that they were perceptually sound, useful for scientific inquiry, and maintained a pleasing aesthetic.

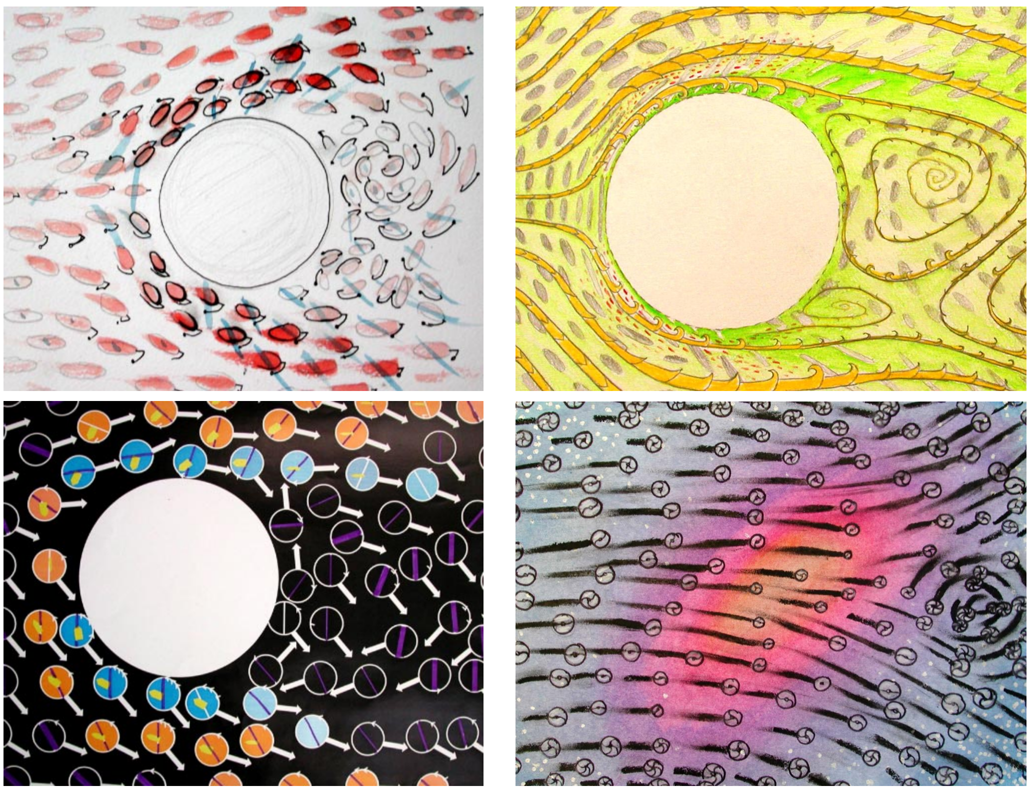

Figure 7: Students in a joint computer science/art scientific visualization class generated creative multivalued 2D flow visualizations.

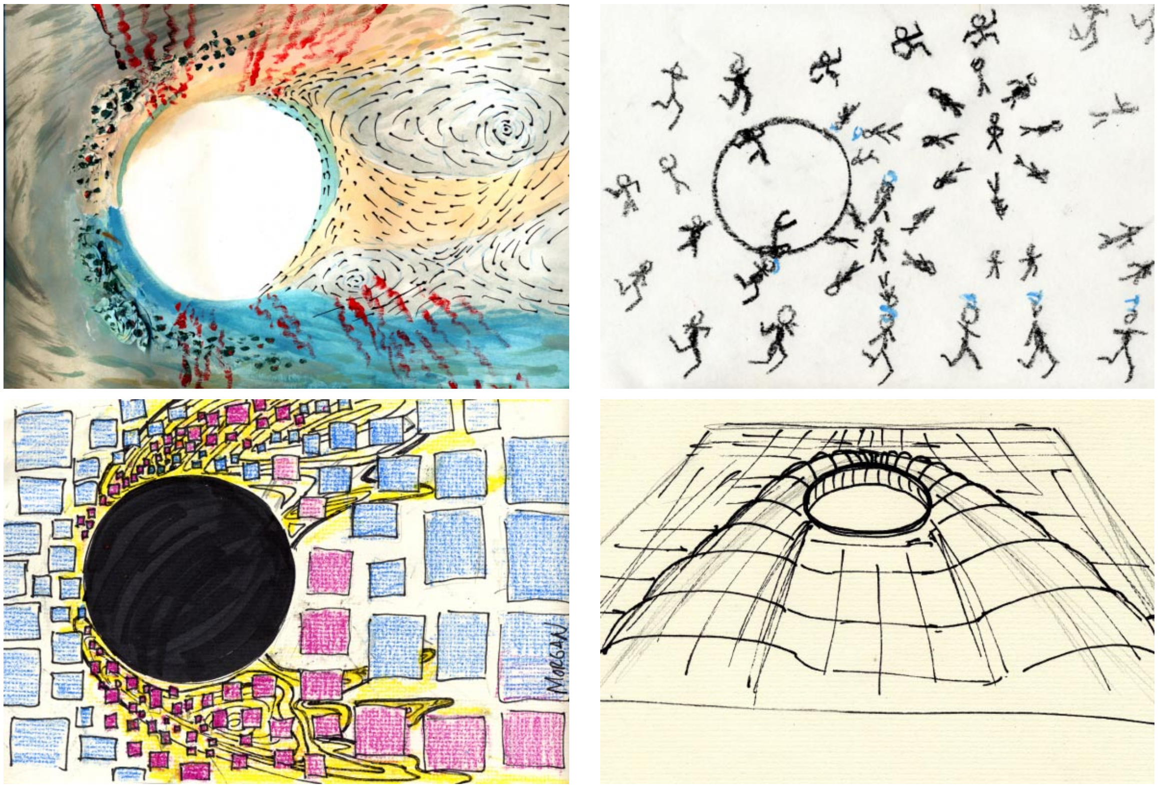

Figure 8: Examples of 2D flow visualizations developed by students in a SIGGRAPH 2001 course.

One conclusion from this class experience is that, particularly in complicated, multi-variate visualization problems, the design process is extremely important. When approaching these difficult visualization problems, it is rare for an initial visualization design to be visually coherent enough for scientists to use successfully. Iterating upon a visualization design takes time. Critiques can certainly help in this process.

Quickly sketching out design ideas and refining them again and again, each time evaluating them from the standpoint of the target audience's scientific goals, is one of the best ways to refine a design. For 2D visualization problems, this is often easily accomplished with traditional artistic tools. In fact, Fig. 8 shows some of the designs that attendees of the SIGGRAPH 2001 course entitled "Non-Photorealistic Rendering in Scientific Visualization" [10] were able to create in an afternoon. These were quick sketches made with paint, markers, etc. They represent experimentation and thinking outside the box. This type of effort is needed for complex visualization problems, the type to which art-based visualization methods are perhaps most suited. When we move to 3D visualization problems, quick sketches and visualization prototypes become much more difficult to make and critique.

2.4 Sketching and Prototyping for Virtual Reality

Currently, it can take a long time to advance from an initial art-based visualization idea sketched out on a piece of paper to a useful visualization. One of the most time consuming parts of this process is refining and iterating on the design; iteration is an essential part of the design process.

For some media, it is important to do much of the refinement step within the final medium itself. For 2D visualizations, this is less of a concern because traditional 2D media can do a fairly complete job of mimicking what can be seen on a computer screen. Thus, visualization designers can sketch out ideas, critique them, and revise them all without the time consuming step of implementing the design on the computer. However, for virtual reality (VR) and other 3D computer mediums, it is difficult to mock up and accurately critique a visualization without actually going through the trouble of programming it and experiencing it. Prototyping designs with traditional 2D and 3D artistic media is still beneficial for VR-based visualizations, but the insight that can be gained from critiquing these prototypes is limited because so many of our physical and perceptual cues change when we enter a virtual environment. Dimension, scale, colors, composition, interaction, and sense of presence all change as we move from a 2D representation of the idea to a complete virtual world.

Recently, we have started to take a new approach to prototyping and design in 3D that mimics a traditional 2D artistic process. The cornerstone of this approach is the Cave-based VR system, CavePainting [15]. CavePainting uses a prop and gesture based interface derived from a traditional oil painting process to allow an artist to paint 3D forms directly in VR using a six degree-of-freedom tracker. While the interaction is based on painting techniques with which the artist is already familiar, the resulting "paintings" are a form of zero-gravity sculpture that bears little resemblance to a flat oil painting. Nevertheless, the quick, loose, stroke based style of CavePainting make it an excellent candidate for testing the feasibility of extending painting inspired visualization techniques to three-dimensional problems and prototyping 3D visualization designs.

Through using this tool, designers have been able to refine 3D visualization techniques quickly from within VR. The immediate advantage of this approach is that designers can visually critique a Cave-based visualization during the early stages of design. At this point in the process, even dramatic changes to the approach are easy to make. In our experience, design changes are often discussed and sketched out in 3D *during* a critique. Our vision for this approach to visualization design is that the ability to more quickly produce and iterate on designs within VR will decrease the time that it takes us to converge on scientifically useful visualizations.

This vision has played out in some of our initial work with the visualization class described above. As we continue to develop this prototyping tool and achieve a tighter coupling with scientific needs, we anticipate that prototyping designs in VR will allow us to spend much more time iteratively designing for VR visualizations and less time implementing complex visualization approaches that eventually prove to be less perceptually sound and scientifically useful than originally planned.

We further explore some of the issues raised in this section after providing historical perspective in the next section.

3 Historical Perspective: The Connections between Art and Science

We now present a historical perspective on the connections between art and science, with particular emphasis on the efforts that have been made over the last ten years to unite scientific visualization with other visual science disciplines. This section is by no means comprehensive; our goal is to provide a broad overview of the current stream of momentum from which painterly methods have derived over the past twenty years or so.

We partition this section into two subsections, a conceptual history and practical connections between art and science. The former traces the steady infusion of artistic ideas and concepts into the scientific visualization community, while the later presents current applications, both explicit and tacit, of painterly concepts in the development of visualization methodologies.

3.1 History of Art-related Scientific Visualization

For at least the last six centuries artists have striven to develop methods for distilling complex scene information into oil painting representations. Some of this work was even directed at scientific topics, including astronomy and fluid flow. Within the last twenty years, there has been a renewed recognition that concepts from art and visual disciplines are not orthogonal to the goals of scientific visualization. Victoria Interrante succinctly presents the similarities and differences between visualization and art in [10]. She states that "Visualization can be viewed as the art of creating a pictorial representation that eloquently conveys the layered complexity of the information in a complicated dataset." In the same article, however, she also emphasizes how visualization and art are different: "Visualization differs from art in that its ultimate goal is not to please the eye or to stir the senses but, far more mundanely, to communicate information - to portray a set of data in a pictorial form that facilitates its understanding. As such, the ultimate success of a visualization can be objectively measured in terms of the extent to which it proves useful in practice. But to take the narrow view that aesthetics don't matter is to overlook the complexity of visual understanding." (C&C REFER TO VICKI'S CHAPTER?)

Early pioneers in this field, such as Donna Cox, who holds positions in both the School of Art and Design and the National Center for Supercomputing Applications at the University of Illinois, Urbana-Champaign, understood the potential of bringing scientists and visual design artists together. In 1987 Cox developed the concept of "Renaissance Teams," a team of domain experts and visualization experts whose goal was to determine visual representations which both appropriately and instructively presented domain specific scientific data.

In her 1995 essay "Art, Science" Vibeke Sorensen, Professor and Founding Chair of the Division of Animation and Digital Arts in the School of Cinema-Television at the University of Southern California, alludes to the necessity of such "Renaissance Teams" to effectively counter the divisional chasm between artistic and scientific disciplines which has been caused by specialization. She argues that in the mind of most scholars, the ideal of the artist-scientist as an integrated, educated individual culminated in Leonardo da Vinci. Da Vinci represents the union of artist and scientist. Although considered by some to be the epitome of the artist-scientist combination, the da Vinci ideal was soon lost to specialization. As our quest for knowledge produced a plethora of different subfields of science, the communication between different disciplines disintegrated, and in particular the ties between art and science were severed in the name of scientific objectiveness. Sorensen, however, asserts in her published articles on art and science, her strong conviction that artists have an important role to play in the further development of science and technology. In particular, that the means of restoring the ideal artist-scientist is through interdisciplinary research collaborations in which there is a synergy of many different disciplines, scientific and artistic.

Over the last several years there have been several attempts to foster this cultural crossover through panels and workshops. For instance, in 1998, David Laidlaw organized a panel at IEEE Visualization 1998 entitled "Art and Visualization: Oil and Water?" [23] whose purpose was to explore such questions as "How can artistic experience benefit visualization?" and "What artistic disciplines have the most to offer?". In 1999 J. Edward Swan organized a panel at IEEE Visualization 1999 entitled "Visualization Needs More Visual Design!" [30] whose purpose was to argue two main points: that utilizing visual design may be difficult but is important for visualization, and that, in general, the scientific community needs to work harder to tap into the many centuries of design knowledge that exists in fields such as art, music, theater, cartography, and architecture. In 2001, Theresa-Marie Rhyne organized a panel at IEEE Visualization 2001 entitled "Realism, Expressionism, and Abstraction: Applying Art Techniques to Visualization" [26] which explored the artistic transition between realism, expressionism and abstraction and attempted to examine if such a progression also exists within the field of scientific visualization. One conclusion of that panel, articulated by Chris Healey, is that "the appropriate use of perceptual cues can significantly enhance a viewer's ability to explore, analyze, validate and discover." In that same year, two SIGGRAPH 2001 courses were dedicated to artistic topics. Sara Diamond organized a class entitled "Visualization, Semantics, and Aesthetics" and Chris Healey organized a class entitled "Nonphotorealistic Rendering in Scientific Visualization," both of which further explored the connection between scientific visualization and artistic sciences. At a different forum, Felice Frankel, a research scientist in the School of Science at the Massachusetts Institute of Technology organized what has been referred to as ground-breaking conference at MIT entitled “Image and Meaning, Envisioning and Communicating Science and Technology” which was an initiative to promote new collaborations among scientists, image experts, and science writers. Her new book captures some of the excitement of the conferences [7]. The following year, at SIGGRAPH 2002 Kwan-Liu Ma organized a course entitled “Recent Advances in Non-Photorealistic Rendering for Art and Visualization” whose expressed purpose was to give a concise introduction to non-photorealistic rendering in the context of generation of artistic imagery and perceptually effective scientific visualization. Along the same lines Non-Photorealistic Animation and Rendering (NPAR) in 2002 had a section specifically devoted to painterly rendering. Though the section was not limited to scientific visualization, its focus was on the exploration of interjecting painterly ideas into the visualization process.

Interest in collaboration between the arts and science has not remained confined to conferences and workshops, but has also spilled over into the archival publication realm. Laidlaw published in [18] an article entitled “Loose, Artistic ‘Textures’ for Visualization” in which he encouraged the scientific community to search beyond what perceptual psychologists understand about visual perception into the fundamental lessons that can be learned from art and art history. Herman and Duke, in their article entitled “Minimal Graphics” [5] explore what can be learned from artistic traditions with respect to representing only salient features in a visualization. Taylor, in his article entitled “Visualizing Multiple Scalar Fields on the Same Surface” [31] reviews and augments with his own work ideas for visualizing multivalued data fields built upon artistic ideas. This small sampling is not meant to be all inclusive, but rather to show that mainstream publishing venues are also seeing the wave of the collaborative mixing of art and science.

In summary, over the past twenty years there have been many efforts to, as Sorensen describes, resurrect the artist-scientist combination found in da Vinci. In our modern times, the process of scientific investigation often requires extensive specialization into the nuances of one particular field of discovery, making a da Vinci-like combination of the artist-scientist in a single personage an extremely difficult, yet worthwhile[36], goal. In today’s world, the synergistic interdependence of “Renaissance Teams”, in which experts from many different disciplines combine their efforts, offers the most likely means for achieving a productive fusion of art and science. Slowly but surely this message is being disseminated through conference panels, workshops, and publications.

3.2 Practical Connections between Art and Science

We now present three areas in which, whether explicitly or tacitly, ideas from painting have been applied to scientific visualization. We categorize these areas as multivalued data visualization, flow visualization, and computer graphics painting. Again, our purpose is not to necessarily provide a comprehensive listing of all scientific visualization efforts which could be classified as exhibiting painterly themes, but rather to illustrate the point that scientific visualization as a discipline has been attempting to answer some of the same questions as other visual art disciplines, namely, how to effectively present information in a form which is comprehensive, yet uncluttered.

3.2.1 multivalued data visualization

Hesselink et al. [11] give an overview of research issues in visualization of vector and tensor fields. While they describe several methods that apply to specific problems, primarily for vector fields, the underlying data are still difficult to comprehend; this is particularly true for tensor fields. ‘Feature-based” methods, i.e., those that visually represent only important data values, are promising.

Statistical methods such as principal component analysis (PCA) [14] and eigenimage filtering [37] can be used to reduce the number of relevant values in multivalued data; often this is a worthwhile tradeoff. In reducing the dimensionality, these methods inevitably lose information from the data. The approach taken in the fluid flow example presented earlier complements these data-reduction methods by increasing the number of data values that can be visually represented.

Different visual attributes of icons can be used to represent each value of a multivalued dataset. In [8], temperature, pressure, and velocity of injected plastic are mapped to geometric prisms that sparsely cover the volume of a mold. Similarly, in [3] data values were mapped to icons of faces; features like the curve of the mouth or size of the eyes encoded different values. In both cases, the icons capture many values simultaneously but can obscure the continuous nature of fields. A more continuous representation using small line segment-based icons shows multiple values more continuously [6].

Layering has been used in scientific visualization to show multiple items; in [12, 13], transparent stroked textures show surfaces without completely obscuring what is behind them. The layering we presented earlier in the fluid flow example is more in the spirit of oil painting where layers are used more broadly, often as an organizing principle.

3.2.2 Flow visualization

A number of flow-visualization methods display multivalued data. The examples in [24, 4] combine surface geometries representing cloudiness with volume rendering of arrows representing wind velocity. In some cases, renderings are also placed on top of an image of the ground. Unlike our 2D examples, however, the phenomena are 3D and the layering represents this third spatial dimension. Similarly, in [34], surface particles, or small facets, are used to visualize 3D flow: the particles are spatially isolated and are again rendered as 3D objects.

A “probe” or parameterized icon can display detailed information for one location within a 3D flow [35]; it faithfully captures velocity and its derivatives at that location, but does not display them globally.

Spot noise [33] and line integral convolution [2] methods generate texture with structure derived from 2D flow data; the textures show the velocity data but do not directly represent any additional information, e.g., divergence or shear. The authors of [33] mention that spot noise can be described as a weighted superposition of many “brush strokes,” but they do not explore the concept. The method presented in the previous fluid flow example takes the placement of the strokes to a more carefully structured level. Of course, placement can be optimized in a more sophisticated manner, as demonstrated in [32].

3.2.3 Computer graphics painting

Reference [9] was the first to experiment with painterly effects in computer graphics. Reference [25] extended the approach for animation and further refined the use of layers and brush strokes characteristic for creating effective imagery. Both of these efforts were aimed toward creating art, however, and not toward scientific visualization. Along similar lines, references [39, 38, 28] used software to create pen and ink illustrations for artistic purposes. The pen and ink approach has successfully been applied to 2D tensor visualization in [29]. In reference [20], painterly concepts were presented for visualizing diffusion tensor images of the mouse spinal cord.

4 Some Open Issues

The previous sections suggest some open issues, which we will discuss in more detail here.

4.1 Evaluation

One of the most difficult aspects of developing new visualization methods is evaluating their success, and this is certainly true for methods that are motivated by painting and art. For many exploratory applications, the best measure of success is the acceleration of scientific discovery and insight in other disciplines, but that is virtually impossible to measure quantitatively even with a crystal ball. Scientific advances are dependent on many factors, and visualization tools are only one. Even a significant increase could be lost in the variance caused by the others.

We must revert to less direct measures. These may be judgments about an algorithm's elegance, simplicity, or speed. They may be about the accuracy or speed of a group of users in performing specific well defined tasks. Or they may be about a visualization's aesthetics, ability to display certain features in data, or appeal to domain scientists.

The first type of algorithmic measure is well understood in computer science. We know elegance and simplicity when we see it, and we can easily measure speed and talk about how it scales with problems size. While these are important, their connection back to how well a tool will advance scientific discovery is tenuous, at best. There has been many an algorithm which has scaled nicely with problem size and yet provided no new insight into the scientific problem that was being visualized.

The second type of measure, results from performance-based user studies, are appealing because they are both quantitative and objective [17]. For example, for six methods of visualizing 2D fluid flow data, we measured user accuracy and performance in locating critical points in 2D flow, identifying their types, and visually creating integral lines [21]. With the results, we compared the six methods and drew some conclusions about which features of each may have accounted for good performance on these specific tasks. On the other hand, a leap of faith is required to generalize these results more broadly to other visualization methods, particularly exploratory ones, or even to other tasks. Finding features faster and more accurately could speed the advance of science, but we cannot know for certain. One clear contribution of these kinds of measures is the very explicit set of visualization goals that must be defined in order to perform tests.

The third type of measure is more subjective. Here we might ask domain scientists whether they like a method or appeal to reviewers to judge whether a certain feature is adequately represented visually and whether that is important. This tends to be faster to evaluate than more formal performance-based user studies and can often evaluate larger conceptual advances, but at the cost of some quantization and objectivity and often with implicit assumptions. For example, domain scientists may understandably be biased against unfamiliar methods, even if the unfamiliar methods will be more effective after a learning period. This kind of measure may come the closest to addressing our original question about advancing science.

All three types of measures have their place. What relates the second and third types is the choices that must be made about the important visualization goals to target and the specific population to evaluate them. With explicit design goals, the third type of measure may be particularly valuable. In fact, this kind of evaluation is very similar to art critiques and has the potential to advance our field more quickly. They can provide measures of new methodology. They can help educate both visualization researchers and designers. And they can help clarify visualization goals. They should be used more broadly and incorporated into what we teach our visualization students.

4.2 Visualization Goals

An essential step in critiquing or evaluating visualization methods is defining explicit visualization goals. Too often visual appeal, or even glitz, is confused with effectiveness. Only explicit goals can be effectively evaluated.

Defining visualization goals is an iterative process and should be driven by the underlying scientific applications [1]. As our understanding of a scientific problem moves forward, so will our design goals for visualization methods to address that problem. Our understanding of visualization will also help us to bring effective methods from one scientific domain to bear on others.

It is important to understand that different scientific questions will imply different visualization goals, sometimes contradictory. No one visualization method is right. Some claim that "more is better." This is likely to be true for some kinds of exploration, but for expository visualizations, "less is more" is more likely true.

4.3 Design, Engineering, and Science Collaborations

Designers, engineers, and scientists are brought together because their skills and their disciplines can benefit from collaborations. For scientists, the benefit of collaboration is the potential for increased scientific understanding that can result from clearer, more perceptually sound visualizations. Artists hold one key to making these visualizations a reality. For artists, the win in scientific visualization collaboration comes in many forms. First, working with scientific visualization opens the door to working with a variety of new media. Virtual reality, volume rendering, and other advanced computer graphics techniques are just beginning to migrate out of the graphics research community. Through visualization research, artists have the opportunity to be at the forefront of learning, working with, and even influencing recently created computer media. As illustrators, artists are also drawn to visualization problems because of the complexity of the situations that they represent. These type of problems are exciting because they push theories of visual representation to their limits. In addition to these factors, art educational institutions are beginning to become interested in scientific visualization collaborations because of the potential job opportunities that may be available for their students in the future. As the embrace of artistic insight continues to grow within scientific fields, we will develop a need for a new generation of artists that are adept at understanding and interacting with scientists and that specialize in illustrating the new scientific phenomenon that our technology helps us to explore.

While there is often some overlap in critical knowledge and techniques within design, art, engineering, and science, the terminology, goals, and methods of each are often as different as they are advanced. In scientific visualization, collaborative efforts require insight, communication, and education from all those involved.

4.3.1 Designer Education

The first area for designers to master when applying their skills to visualization problems is the new media that they may be using. Computer graphics in some form are now common at most design schools. In our experience, most potential design or illustration collaborators are familiar with programs such as Adobe Photoshop and occasionally a 3D modeling package. However, many of the visualization approaches where designers can be most helpful to scientists today utilize more recent computer graphics techniques such as volume rendering or virtual reality environments. Many basic design principles transcend the differences between various media, but clearly some time is needed for designers to experiment and eventually become proficient within a new medium.

Prototyping systems, such as the CavePainting-based virtual reality system described in Sec. 2.4 offer a transitional tool for designers. Designers are given an intuitive interface for creating VR worlds that can be targeted towards an artistic purpose or a scientific design. This allows for experimentation and gives designers a chance to learn the properties and limitations of a medium that they might not have without becoming proficient graphics programmers. There is much room for experimentation here in creating tools for quickly iterating on complicated interactive 3D visualizations.

In addition to learning how to use new media, designers must also learn the language and goals of their collaborators' disciplines. Understanding the scientific goals behind a visualization is the most important element for designers to grasp. It is nearly impossible to create a good visualization when you do not know what you are trying to show. This does not mean that the designer needs to be an expert in the scientific field. This is an unrealistic goal, but designers must be prepared to work with scientists to understand their goals and needs. This can be a difficult process as the languages of the two disciplines are often quite different.

For example, to a scientist looking at a point in a visualization, “value” means 10 meters per second, a measurement of an experimental quantity. To an artist, “value” means the lightness or darkness of the region. Even simple conversations can become exercises in creating a common language of communication.

Cross-discipline initiatives such as the Brown University and Rhode Island School of Design (RISD) cross-registered course, “Interdisciplinary Scientific Visualization,” and RISD’s newly created program in digital media will help to tighten the threads connecting the art world and the visualization community. These ventures, and similar ones at other institutions, will help to develop a language for collaboration and teach scientists, engineers, programmers, and artists to understand each others’ goals and work together, as in Donna Cox’s renaissance teams, to realize their designs.

4.3.2 Engineering and Scientific Education

As for designers, it is important for scientists, engineers, and programmers to not only master the new media that computers provide but also understand the scientific goals behind the visualization. The mastery of computer media should cover potential uses of current hardware and software solutions. It is also important for the computer experts in a collaboration to provide tools to other collaborators that they can use. This may be as simple as providing digital or physical printouts of imagery. It may be complex as a virtual reality prototyping system. It is imperative that engineers and programmers find the means for including scientists and designers in the design loop. Technological barriers often make this difficult. However, any visualization collaboration will be enhanced by quickly establishing a means for overcoming the obstacles to communication and design input presented by differences in computing facilities and experience.

Finally, it is critically important for scientists to appreciate design and the aesthetic sense that designers have developed through their training and experience. This leads to a recognition of the potential that design has for furthering scientific discovery, a necessary ingredient for a successful collaboration. Often, this appreciation is best accomplished through experience in artistic projects and classes.

4.3.3 Education and the Renaissance-Person

Most of the scientific visualization approaches we have discussed to this point involve significant interdisciplinary collaboration by multiple people. It is interesting to note that what this approach strives to create through collaboration is the equivalent of a Leonardo da Vinci: a scientist and artist acting as one. Artistic insight feeds into and illustrates scientific discovery, while scientific discovery pushes the limits of artistic representation and understanding. In a sense, there is a continuum between science and art, and each individual spans some portion of that continuum. The more that one learns about the other’s field, the more of the continuum one covers. As scientists learn more about design and art through collaborations, classes, and experience, they break down the barriers between the two disciplines, develop a new visual language and understanding, and make it easier for the collaborative processes to succeed. The same is true for artists and designers. As they come to understand science and its goals, they become, more and more, renaissance-people, spanning the entire continuum. Perhaps only a very few will reach da Vinci status, but the future collaborations of all who strive to understand their collaborators’ fields will be enhanced by their increased knowledge.

As interdisciplinary initiatives continue to grow in universities and research settings world wide, we are beginning to see a change in the way science and art are taught. There is a tighter bond between the two and a greater appreciation for how the two disciplines can work together to help achieve the goals of each. By structuring our teaching to embrace this principle, we have the ability to foster a new generation of renaissance-people and skilled collaborators.

5 Summary

In this chapter we have narrated some of our own experiments with merging concepts from art and design into the scientific visualization process, particularly for exploratory applications that work with multivalued data. We have also surveyed related work to give some context for others aiming to continue explorations into the synergy between these two disciplines. It is clear to us that there remains much visualization knowledge to mine from the world of painting, art, and design. Some of this knowledge is about visual representations, but there are design and pedagogical components as well that will play a role in educating visualization researchers and in evaluating visualization methods. Collaboration in the form of renaissance teams and the development of renaissance scholars will advance our field, and tools that amplify the output of designers by better leveraging their design capabilities without taxing their stamina and patience will be critical to this advancement.

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