Editors: Theresa-Marie Rhyne and Lloyd Treinish

Loose, Artistic "Textures" for Visualization

David H. Laidlaw

Brown University

In the November/December 2000 issue of *IEEE Computer Graphics and Applications*,[1] Vicki Interrante posed a visualization problem she and I have been interested in for several years. The problem is that of visually representing a 2D field of data that has multiple data values at each point. For example, 2D fluid flow has a vector value at each location and derived values are often available at each location. Interrante suggests using natural textures to attack this problem, because the textures can potentially encode lots of information. She provides some intriguing examples and proposes a psychology-based approach for developing an understanding of how we perceive natural textures, like those Brodach photographed.[2] Understanding this helps us build better visualizations.

Based on Interrante's suggestions, I would like to posit and explore what is, perhaps, a less well-defined approach. Through evolution, the human visual system has developed the ability to process natural textures. However, in addition to natural textures, humans also visually process man-made textures—some of the richest and most compelling of which are in works of art. Art goes beyond what perceptual psychologists understand about visual perception and there remain fundamental lessons that we can learn from art and art history and apply to our visualization problems.

The rest of this article describes and illustrates some of the visualization lessons we have learned studying art. I believe that these examples also illustrate some of the potential benefits of further study. While this approach is more open-ended than a perceptual psychology approach, both approaches are worthy of pursuit, and the potential benefits of using the less structured approach outweigh any risk of failure.

How humans see and understand

Scientific visualization, a term coined only a little over 10 years ago, is the process of using the human visual system to increase our understanding of phenomena studied in various scientific disciplines. While the term is young, the process (modulo the computer) has been used since the beginning of science. Many scientists have created drawings or built 3D models to understand and communicate their science. The history of science and art can provide us with lessons for using computers effectively. Over time, artists have developed techniques to create visual representations in particular communication goals. Art history provides a language for understanding and communicating that knowledge.

Historically, two disciplines approach the human visual system from different perspectives. Art history provides a phenomenological view of art—painting X evokes response Y. Art history, however, doesn't deconstruct the perceptual and cognitive processes underlying responses. Perceptual psychology, on the other hand, strives to explain how humans understand those visual representations. There's a gap between art and perceptual psychology—we don't know how humans combine visual inputs to arrive at the responses art evokes. Shape, shading, edges, color, texture, motion, and interaction are all components of an interactive visualization. But how do these components interact and how can they most effectively be deployed for a particular scientific task? Answers to these questions are likely to fill some of the gap between art and perceptual psychology. As an example, the human-computer interaction (HCI) community is using and extending knowledge about perception to test and develop better user interfaces. We can find analogous inspiration for improved methods for scientific visualization in the gap between art and perceptual psychology. Many of these lessons will impact the visual representation of multivalued data.

Looking up from our monitors

A number of times over the last few years I've shepherded my students to art museums for guided tours by my artist collaborator davidkremers, the Caltech Distinguished Conceptual Artist in Biology. After initially searching for scientific visualization inspiration in art, these visits let us formulate a plan for finding and applying the concepts. Our initial focus was on oil painting, particularly from the Impressionist period, because these paintings are so visually rich. The multiple layers of brush strokes in these paintings provide a natural metaphor for constructing visualizations from layers of synthetic "brush strokes." Some of my colleagues look at me askance when I describe our research field trips, as if to say, "This is research?" But stepping out of the lab helps students build a new picture of what they can accomplish when they come back to the computer. It trains their eyes and minds to see differently.

During these field trips, we studied, in particular, the works of three painters:

- Van Gogh, whose large, expressive, discrete strokes carry meaning both individually and collectively.

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(a) (b)

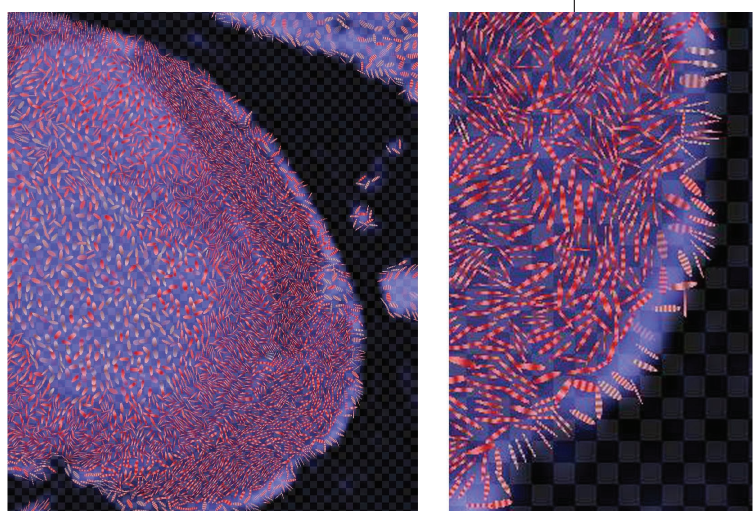
1 **(a) Van Gogh's *The Mulberry Tree* (1889, oil on canvas) illustrates the visual shorthand that van Gogh used with his expressive strokes. Multiple layers of strokes combine to define regions of different ground cover, aspects of the hillside, and features of the tree. (b) An underpainting shows the "anatomy" or composition of the scene in broad strokes. (Image of *The Mulberry Tree* granted by the Norton Simon Foundation, Pasadena, California. Gift of Norton Simon, 1976.)**

- Monet, whose smaller strokes are often meaningless in isolation—the relationships among the strokes give them meaning, far more than in van Gogh.
- Cezanne, who combined strokes into cubist facets, playing with 3D perspective and time within his paintings more then either van Gogh or Monat. His layering also incorporates more atmospheric effects. In a sense, his work shifts from surface rendering toward volume rendering.

The three artists' work in this sequence builds in complexity and subtlety. In our field trips, we studied all three, but most of our experiments thus far are limited to ideas we learned from van Gogh's work.

Van Gogh introduced us to the concept of underpainting, or laying down a rough value sketch of the entire painting. The underpainting shows through the overlying detailed brush strokes to define the anatomy of the painting. Figure 1b shows underpainting for Figure 1a. It divides the canvas into two parts—a primed lower region of hillside, rocks, and ground cover and a darker upper region of tree, sky, and distant hills. Underpainting helped us present some overall parts of our data. We found that an analogous underlying form in our visualizations anchors and literally gives shape to disparate data components. Outlines around regions provide separation and emphasis, lending definition to our sea of data.

In van Gogh's *The Mulberry Tree* (1889, oil on canvas), brush strokes represent the solid trunk of the tree, bending branches, leaves blowing in the wind, and tufts of grass (Figure 1a). We learned many shorthand ways of depicting complexity using icons, geometric shapes, or textures that evoke a characteristic of the subject, or the data—and with that comes the responsibility of choosing brush strokes that don't create opposing or unwanted secondary impressions. Beyond this direct representation, they also invite the viewer to experience the scene, not just view it passively. Similarly, brush-stroke size and proximity depict density, weight, and velocity. In our visualizations, we want to capture this marriage between direct representation of independent data and the overall intuitive feeling of the data as a whole.

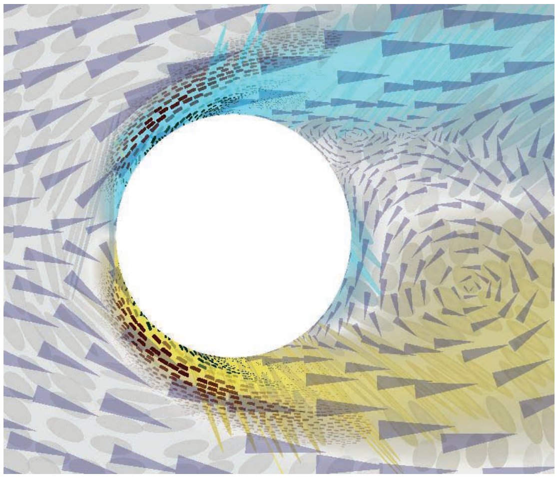


2 **Visualization of half of a section through a mouse spinal cord. The data is a symmetric 3D second-order tensor field, with the equivalent of six independent scalar values at each point. The detail on the right shows the lower right part of the section.**

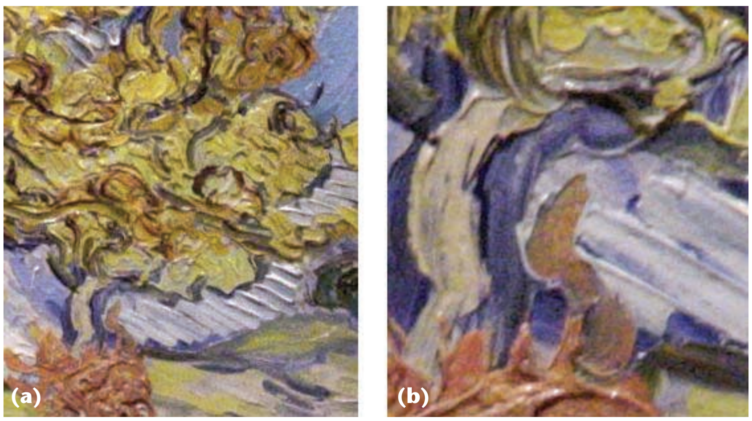
Back in the lab

Returning to our computer lab, we tried to use some of the ideas we had gleaned, once again drawing mostly from van Gogh's work. We experimented with brush stroke shapes and ways of layering them. Our initial attempts were free–form and produced interesting results. Our next attempts were more directly applied to scientific problems. We show two of the images we generated in Figures 2 and 3 (next page). The problem-directed approach led us to iconic-looking strokes.

In Figure 2, we show one 2D slice of a 3D second-



3 Visualization of 2D fluid velocity together with several derived data values. Approximately nine values are represented visually at each point in the image.



4 Variances in viewing van Gogh's *Mulberry Tree*. Viewed in this article from about 18 inches, Figure 1a shows what you would see 15 feet from the painting. Comparatively, Figure 4 shows the following: (a) a detail of what you would see 5 feet from the painting, and (b) a detail at actual size (what you would see from 18 inches). Look at (b) more closely for viewing distances less than 18 inches.

order tensor field, which has about six different data values at each point in the image. The image shows the right half of a section through a mouse spinal cord. To create the visualization, we used a layer resembling underpainting with ellipse-shaped strokes on top of it. On each of the strokes, a texture represents more of the data. For more details on the scientific interpretation and the visualization, see Laidlaw et al.[3]

In Figure 3, we show 2D fluid velocity together with a number of derived quantities. About nine values are represented at each spatial location in this visualization. We again used a layer resembling underpainting with layers of ellipse, wedge, and box strokes on top. The ellipse strokes have a subtle texture superimposed. More details on the visualization appear in Kirby et al.[4]

Space

We learned that paintings (and, in some cases, visualizations) are multiscale. They can be viewed from different distances and seen and understood differently. This raises interesting issues about the definition of texture. Let's consider van Gogh's *Mulberry Tree* (Figure 1a). From a few inches away (look closely at Figure 4b), you can see shapes from the bristles of the brush as well as colors mixed within a stroke. At this distance, the shape and color features might be considered texture, but they could also be interpreted individually. At a distance of 18 inches (Figure 4b at a normal reading distance of 18 inches), these features appear smaller and resemble a texture on each stroke. The strokes themselves are still individual. At a distance of five feet (Figure 4a), the strokes merge together to appear more like a texture. Finally, at 15 feet (Figure 1a), the strokes blend together and become almost invisible individually.

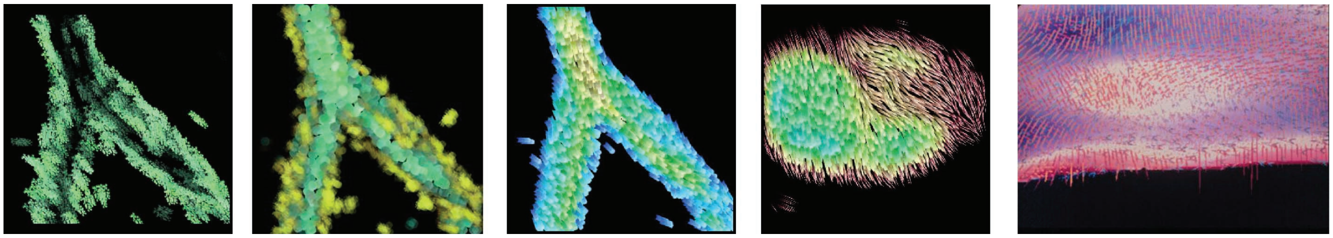
We can use this lesson by encoding different information at different scales. Iconic information at one scale can turn into texture information at another scale. With care, we can design features at different scales into the same images. In the scientific visualizations of Figures 2 and 3, we design visual features at different scales. The texture on strokes is at a much finer scale than the strokes themselves, and the dark box strokes of Figure 3 are at a different scale than the other strokes.

To take full advantage of the multiscale nature of paintings and visualizations we have to have ways of interacting with them—that is, ways of changing our viewing distance. We rarely change the distance from which we view our monitors—only a bit more frequently do we do so with paper publications. That's why the same image is shown at different scales in Figure 4 and in some of the other detailed figures. However, we do view images hung on a wall from different distances. And some images on paper—often artistic—inspire that sort of study. Projection systems like PowerWalls and CAVEs may be good options for encouraging this sort of exploration, as may other hangable large-format output media.

Time

We also learned that paintings (and, in some cases, visualizations) have a temporal component. For instance, we see different aspects of an image at different viewing times. Some parts stand out quickly, like the overall composition or palette of a painting, and some take more time to become apparent, like the texture or shape of individual strokes. The scale and speed of recognition correlate, as do contrast and speed of recognition—but these are not the only factors.

To use this lesson, we can design our visualizations so that important data features are mapped to quickly seen visual features. For example, features we want to measure directly from an image are present for detailed study but don't intrude on the visualization's initial impression. The multiscale examples from the "Space" section illustrate this temporal concept. Figure 3 gives another example: we can read the wedges more quickly than the



5 **Loose texture examples.**

ellipses because of a difference in contrast.

Studies of preattentive vision and knowledge about low-level vision are useful for designing quickly seen visualization parts. It's more difficult to test the more slowly seen parts, which makes it more difficult to design them. Task-oriented experimental tests seem logical, but the tasks are often so complex that the performance variance is relatively high, making methods difficult to compare.

Our initial experiments

Our initial experiments were much looser than the examples shown in Figures 2 and 3. Some examples in Figure 5 show 2D or 3D fluid flow. Since I want to emphasize the overall texture and visual qualities, I won't go into detail about the mappings for each. To many, the images are visually compelling, yet it has been difficult to extract concrete visualization lessons from them beyond those I previously described. What people see in these images includes not only the mappings that were used for the data value, but also other visual characteristics. Despite being 2D, some images give an overall sense of depth. Some of the strokes appear to layer, like feathers or scales. One of our challenges with these looser images is in understanding what works, what doesn't, and (we hope) why.

Closing thoughts

I've tried to illustrate some examples of looking toward art for inspiration in creating visualizations. Here we feature van Gogh and mention Monet and Cezanne for context. In your artistic searches, choose the artists in whom you have a passionate interest. I believe that any artist has lessons to offer to visualization.

Working on scientific visualization problems, we already interact with scientists and adopt their problems. As toolsmiths, we do better computer science through addressing scientists' problems on scientists' terms.[5] Similarly, we benefit from critical feedback from artists, despite the difficulty of creating and maintaining these relationships. I try to look at and understand art—early and often—and emulate it in scientific visualizations and get critical feedback from artists. I explain what I'm trying to do visually and have artists critique it. Then I iterate, iterate, and iterate.

Of course, scientists must be involved in this iterative process. Artists can help with inspiration and feedback on the visual and communicative aspects of visualization, but scientists define the tasks performed and therefore must ultimately evaluate the success of the methods. For instance, the fluid flow example in Figure 3 may be aesthetically pleasing, but without explanation—perhaps via a legend or key—it's not scientifically useful.

Figure 3 displays as many as nine values at each point of the image. With some research indicating that texture has roughly three independent dimensions, the ability to represent nine values is somewhat surprising—perhaps it's due to combining color with texture or layering textures at different scales.

Texture is hard to define. Understanding black and white natural textures like the photographs in Brodatz[2] is a good start, but we also need to look broadly. Task-oriented user testing may help, and perhaps we can use the critiques that are part of artists' training. This might combine perceptual psychology and art to fill in part of the gap in our understanding of how humans see. By having artists cognitively analyze what is shown by more complex textures, we might come to a consensus on what works, what doesn't work, and why it does or doesn't work in the context of art and art history. ■

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Readers may contact Laidlaw at the Department of Computer Science, P.O. Box 1910, Brown University, Providence, RI 02912, email dhl@cs.brown.edu.

Readers may contact department editors Rhyne and Treinish by email at rhyne@siggraph.org and lloydt@us.ibm.com.