

# Visualization Viewpoints

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## Perception and Painting: A Search for Effective, Engaging Visualizations

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Scientific visualization represents information as images that let us explore, discover, analyze, and validate large collections of data. Much research in this area is dedicated to designing effective visualizations that support specific analysis needs. Recently, though, we've considered visualizations from another angle. We've started asking, Are visualizations beautiful? Can we consider visualizations works of art?

You might expect answers to these questions to vary widely depending on an individual's interpretation of what it means to be artistic. We believe that the issues of effectiveness and aesthetics may not be as independent as they seem initially. We can learn much from studying two related disciplines—human psychophysics and art theory and history. Human psychophysics teaches us how we see the world around us. Art history shows us how artistic masters capture our attention by designing works that evoke an emotional response. The common interest in visual attention provides an important bridge between these domains. We're using this bridge to produce effective and engaging visualizations, and we'd like to share some of the lessons we've learned along the way.

### Multidimensional visualization

Through our lab work, we've studied various issues in scientific visualization for much of the last 10 years. A large part of our effort focused on multidimensional visualization, the need to visualize multiple layers of overlapping information simultaneously in a common display or image. We often divide this problem into two steps:

- the design of a data-feature mapping  $M$ , a function that defines visual features (such as color, texture, or motion) to represent the data and
- an analysis of a viewer's interpretation of the images  $M$  produces.

An effective  $M$  generates visualizations that let viewers rapidly, accurately, and effortlessly explore their data.

One promising technique we discovered is using results from human perception to predict the performance of a particular  $M$ . The low-level visual system identifies certain properties of what we see very quickly, often in only a few tenths of a second or less. Perhaps more importantly, this ability is display-size insensitive, so visual tasks are completed in a fixed length of time

that's independent of the amount of information being displayed. Obviously, these findings are attractive in a multidimensional visualization context. We can combine different visual features to represent multiple data attributes and pack large numbers of multidimensional data elements into an image. A viewer then rapidly analyzes sequences of images in a movie-like fashion.

Figure 1 shows two example visualizations of multidimensional weather data. We constructed the first image by taking traditional visualizations of each attribute, then compositing them. Hue represents temperature (yellow for hot, green for cold), luminance represents pressure (bright for high, dark for low), directed contours represent wind direction, and Doppler radar traces represent precipitation. We built the second image using simulated brush strokes that vary their perceptual color and texture properties to visualize the data. Here, color represents temperature (bright pink for hot, dark green for cold), density represents pressure (denser for lower pressure), stroke orientation represents wind direction, and size represents precipitation (larger strokes for more rainfall). Although viewers often gravitate toward the first image because of its familiarity, any attempt to perform real analysis tasks leads to a rapid appreciation of the careful selection of colors and textures in the second image. Our experiments showed that viewers prefer the second image for the vast majority of the tasks we tested.

Using perceptual guidelines can dramatically increase the amount of information we can visualize. We can't take advantage of these strengths with an ad-hoc choice of  $M$ , however. Certain combinations of visual features actively mask information by interfering with our ability to see an image's important properties. A key goal, therefore, is to build guidelines on designing effective visualizations and to present these findings in a way that makes them accessible to other visualization researchers and practitioners.

During the last year, we asked ourselves, How can we make our visualizations engaging or aesthetically pleasing? Although this issue has only recently received attention in the visualization community, we feel it's an important factor worthy of study. An image regarded as interesting or beautiful can encourage viewers to study it in detail. We might use stylistic techniques that capture and focus attention on certain areas of a painting to

highlight important or unexpected properties in the data. We expect the lessons learned from studying the work of master painters to have a significant impact on the quality of visualizations we produce.

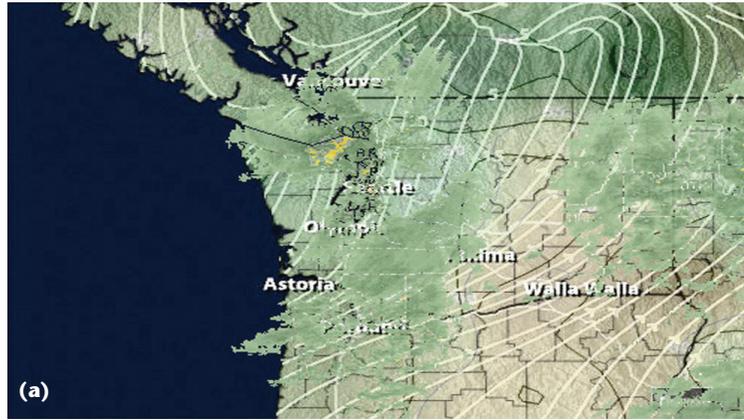
### Visual perception

At first glance, the areas of perception and painting might appear completely independent of one another. However, we found an important overlap between the brush style properties in Impressionist painting and the fundamental visual features detected by the low-level visual system. This correspondence between low-level visual features and painterly styles is critical for our work, because it lets us design effective and aesthetic visualizations.

One of the most important lessons of the past 25 years of research in psychophysics is that human vision doesn't resemble the relatively faithful and largely passive process of modern photography. The goal of human vision isn't to create a replica or image of the seen world in our heads. A much better metaphor for vision is that of a dynamic and ongoing construction project, where the products being built are short-lived models of the external world that are specifically appropriate for the viewer's current visually guided tasks. It would appear that humans don't have general-purpose vision. What we see when confronted with a new scene depends as much on our goals and expectations as it does on the array of light that bombards our eyes.

Among the research findings responsible for this altered view of seeing is a greater appreciation of the following:

- Detailed form and color vision is only possible for a tiny window of several degrees of arc surrounding your current gaze location. Seeing beyond the single glance therefore requires a time-consuming series of eye movements.
- Eye movements required for seeing a whole scene—such as the 180-degree view we often assume we have—are discrete. Our eyes must make many movements to see the detail in a large scene and we gain almost no visual information during an eye movement itself.
- Memory for information in one glance to the next is extremely limited. At most, we can successfully monitor the details from only three or four objects between glances. Often perception is limited to only a single object at a time. What we see therefore depends critically on which object(s) in a scene we're looking for and attending to.



**1** Two examples of visualizing weather conditions: (a) traditional visualizations for each attribute composited into a single image and (b) simulated brush strokes that vary their color and texture to visualize the data.

- Human vision is designed to capitalize on the assumption that the world is generally a quiet place, so we only register differences. Objects that are different from their surroundings, or that change or move, draw attention to themselves because of the difference signals that emanate from these visual field locations.
- Few basic visual features exist that we can use to guide attention. These features include differences in the first order properties of luminance and hue and the second-order properties of orientation, texture, and motion. Effective third-order properties are limited to simple properties of shape such as length, area, and convexity.

We can illustrate the reality of each of these findings through the so-called change blindness that affects us all.<sup>1</sup> It involves a task similar to a game that has amused children reading comic strips for many years. Try to find the difference between the two pictures in Figure 2 (next page). (Hint: look at the bushes immediately behind the Sphinx.) Many viewers have difficulty seeing any difference and often have to be coached to look carefully to find it. Once they've found it, they realize that the difference isn't subtle. Change blindness isn't a failure to see because of limited visual acuity; it's a failure based on inappropriate attentional guidance. Some parts of the eye and the brain are clearly responding differently to the two pictures. Yet, this doesn't become part of our visual experience until we focus our attention directly on the objects that differ.

2 An example of change blindness, the inability to quickly identify significant differences across separate views of a common scene. Try to identify the difference between the two photographs.



Courtesy of Ron Rensink

3 A close-up view of an oil painting that demonstrates various stroke styles, such as color, path, size, and density.



Courtesy of Laura Tateosian

Harnessing human vision effectively for data visualization purposes therefore requires that we construct displays that draw attention to their important parts. Because the displays are typically novel, we can't draw on the expectations that might accompany viewing a familiar scene. Rather, we must rely on an effective mapping between data values and features, so that differences in the visual features draw the eyes—and more importantly, the mind—on their own. Luring the viewer's eyes to a particular object or location in the scene is the first step in having the viewer form a mental representation of that part of the scene that may outlast the next glance or scene that comes into view.

### Nonphotorealistic visualization

Our interest in artistic visualizations naturally led us to explore in two directions: nonphotorealistic rendering in computer graphics and art history and art theory discussions of known painterly styles.

Nonphotorealistic rendering converts pictures or 3D geometric scenes into nonphotorealistic images. Rather than trying to generate results that are indistinguishable from photographs of an equivalent scene (for example, photorealistic rendering), nonphotorealistic techniques draw their inspiration from artistic works (see Figure 3) to produce pen-and-ink sketches; cartoons; or paintings that simulate pencil and charcoal, watercolor, and oil-based brush strokes.<sup>2</sup> The proper use of these strokes results in images that guide the eye much more effectively than realistic photographs, in part because artists can make large differences in visu-

al properties coincide with scene locations that they wish to have the viewer spend the most time examining. Some visualization researchers have already started using these ideas as inspiration for painterly visualization techniques.<sup>3,4</sup> We're focusing on methods that use collections of simulated brush strokes to produce a nonphotorealistic image. We plan to visualize a multidimensional data element with one or more brush strokes, where the attribute values embedded in the element control the stroke's visual properties.

Our study of painterly styles from art history was initially restricted to the Impressionist movement. (This term was attached to a small group of French artists—initially including Monet, Degas, Manet, Renoir, and Pissarro, and later Cézanne, Sisley, and Van Gogh, among others—who broke from the traditional schools of the time to approach painting from a new perspective.) Our decision to study the Impressionists was motivated in part by a need to narrow our initial focus to a single painting style; in part by the Impressionists' careful study of color, light, and objects in their paintings; and in part by a personal appreciation of these artists. Properties of hue, luminance, and lighting were explicitly controlled and even studied in a scientific fashion by some Impressionists.<sup>5</sup> Other distinctive examples of the artists' painterly styles include the path of the brush strokes (such as straight or curved), their length and density, the brush used (which affected the strokes' coarseness), and the weight of paint applied to each stroke.

We observed that many of the styles we discovered had a close correspondence to visual features from our perceptual visualizations. For example, color and lighting in Impressionism have a direct relationship to the use of hue and luminance in visualization. Other styles like path, density, and length have partners like orientation, contrast, and size in perception. Taking this into account, we used the following strategy to produce an effective and aesthetic visualization:

- Produce a data-feature mapping  $M$  that uses the perceptual color and texture patterns that best represent a particular dataset and associated analysis tasks.
- Swap each visual feature in  $M$  with its corresponding painterly style.

- $M$  now defines a mapping from data to painterly styles that controls the visual appearance of computer-generated brush strokes; apply this mapping to produce a painted representation of the underlying dataset.

This strategy successfully generated painterly visualizations of multidimensional data. However, we were still left to wonder if our visualizations were effective or aesthetic.

### Effectiveness

The guidelines we use to build our perceptual visualizations come from psychophysical experiments<sup>6</sup> that measure the absolute performance of different visual features, and the interactions that occur between them. We conducted a similar set of experiments but with simulated brush strokes substituted for the original perceptual glyphs. This produced painterly images with strokes that varied in their color, orientation, density, and regularity of placement.

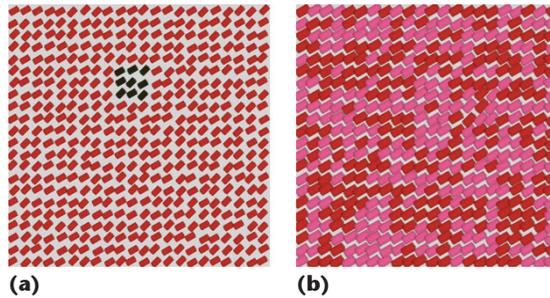
Figure 4 shows examples from the experiments we ran. Half of the displays contained a randomly located group of target strokes defined by a difference in a target style (such as color in Figure 4a and orientation in Figure 4b). Some displays randomly varied a background style (such as orientation during the search for a color target in Figure 4a, and color during the search for an orientation target in Figure 4b). This let us test for visual interference, a situation where variations in a background style inhibit a viewer's ability to identify the target. We showed each display to a viewer for 200 milliseconds, after which we cleared the screen. We then asked the viewer to answer whether a target group of strokes was present or absent in the display.

Our analysis of viewer accuracy mirrored the findings from our original visual perception experiments (see Healey et al.<sup>6</sup> for a complete explanation of these results). Salient features in our original perceptual visualizations were salient in the painterly images. Interference patterns were also identical. This suggests we can use our existing rules of perception to build painterly representations to effectively visualize values in an underlying dataset. It also suggests that any new guidelines we discover could be extended to our painterly environment.

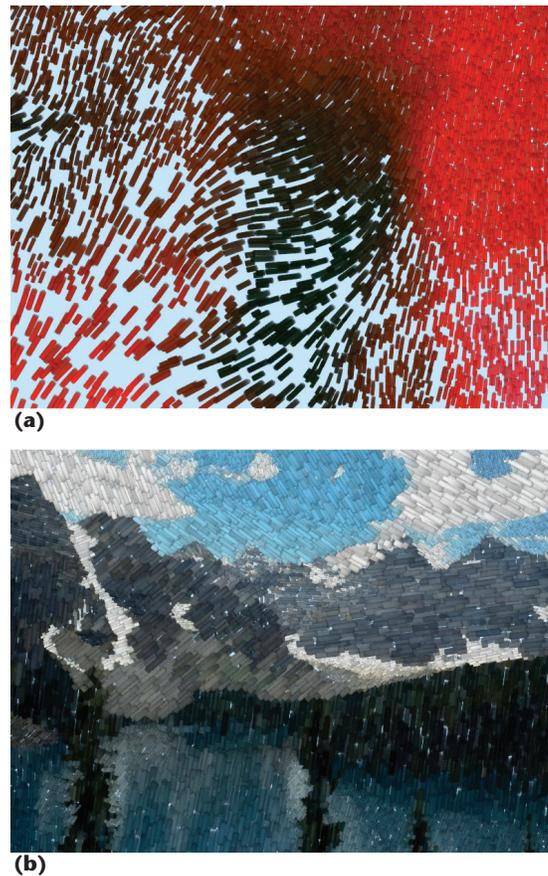
### Aesthetics

Although our initial experiments showed that our painterly visualizations are effective, we still had no evidence of their aesthetic merit. We ran a new set of experiments designed to investigate this property. With these experiments, we asked three questions:

- How artistic do viewers judge our painterly visualizations relative to paintings by artistic masters?
- Can we identify any fundamental emotional factors that predict when viewers will perceive an image as artistic?



4 Example displays from our effectiveness experiment: (a) green target in orange strokes, random background orientation, dense packing, and irregular placement; (b) 45-degree target in 30-degree strokes, random background color, very dense packing, and irregular placement.



5 Example displays from the aesthetic judgment experiment: (a) a painterly visualization of weather conditions and (b) a nonphotorealistic rendering of a photograph of Lake Moraine in Banff, Canada.

- Can we categorize individual viewers as preferring different types of art (for example, Realism or Abstractionism), and if so, how do these preferences impact the emotional responses that predict artistic rankings?

In our experiments, we asked viewers to order 28 images on a scale from 1 (lowest) to 7 (highest). We presented seven images from four different categories: master Impressionists (impressionism), master Abstractionists (abstractionism), nonphotorealistic renderings (nonphotorealism), and painterly visualizations (visualization).

Figure 5a shows an example of the painterly visualizations we tested. Although the visualizations were showing real weather conditions (we represented temperature by color, wind speed by coverage, pressure by size, and precipitation by orientation), we provided the viewers with no explanation about what they depict. We were careful to zoom in to a point where viewers wouldn't

interpret the image as part of a map. We classified these images as abstract in nature, because they had no obvious relationship to a real-world object or scene. We paired them against seven reproductions of real paintings by master Abstractionists: one painting each by de Kooning, Johns, Malevich, Mondrain, and Pollock, and two paintings by Kline.

Because we derived many of our original painterly styles from the Impressionists, we wanted to include their works in our experiment. We picked seven paintings: one each by Cézanne, Monet, Morisot, Pissarro, Seurat, Sisley, and Van Gogh. We counterbalanced these paintings with seven nonphotorealistic renderings. Figure 5b shows one of the renderings—a picture of a mountain lake. We based these images on underlying photos and applied exactly the same brush strokes and painting scheme that we used to generate our painterly visualizations. This was easy to do because a photo is also a dataset with three dimensions: red, green, and blue.

We asked viewers to rank the 28 images for five different questions. The first asked about the images' artistic merit. We designed the other four to probe a viewer's emotional responses. Each ranking was conducted in a similar fashion. For example, during the ranking of artistic merit, we asked viewers to look at the images this way:

As a first step, I would like you to look through this entire set of pictures in order to choose one picture that you like the best. This is a picture that you would like to place as art somewhere in your house or at your place of work. It's the one you think is the best example of good art.

Now look through the remaining pictures and choose the one that you think is the worst example of art.

I would now like you to go through the rest of these pictures in the order in which they come up and assign each one a number from 1 to 7. If the picture is as good as the one you chose to be best, then give it a 7. If it is as bad as the one you chose to be worst, give it a 1. If it is somewhere in-between, then choose an appropriate number between 1 and 7. Remember, 7 represents the best art. Please use the whole range of numbers to the best of your ability.

The remaining four questions asked viewers to do an identical ranking based on how emotionally pleasing the images were (emotionality), how active they were (arousal), how much meaning they contained (meaning), and how complex they were (complexity). We selected the first two questions using the emotional circumplex, a theory that models eight basic human emotions around the two orthogonal dimensions of pleasure and arousal.<sup>7</sup> We designed the second two questions to measure composition around the two dimensions abstract-real and visual complexity.

Although our results are still preliminary, we have already discovered several interesting and exciting findings. Of the 25 viewers we tested, 20 ranked the master

Impressionists as most artistic, followed by the nonphotorealistic renderings, then the master Abstractionists and painterly visualizations. These viewers consistently preferred realistic images over abstract ones. In fact, they judged the nonphotorealistic images as more artistic, on average, than the Abstractionist paintings. This wasn't because the viewers felt that abstract images were completely lacking in artistic merit (the abstract images received an average rank of 2.97). They simply preferred realism to abstractionism. Emotionality and meaning predicted 90 percent of the variance in viewer responses. If viewers who liked realism found an image pleasing and meaningful, they felt it was highly artistic.

Five of our viewers had a different set of rankings. They judged the painterly visualizations as most artistic, followed by the master Abstractionists, then the master Impressionists and nonphotorealistic renderings. These viewers clearly preferred abstract images to realistic ones, ranking the visualizations as more artistic than the Impressionist paintings. For these viewers, arousal was the most important predictor of artistic merit. When they found an image active, they tended to feel it was highly artistic.

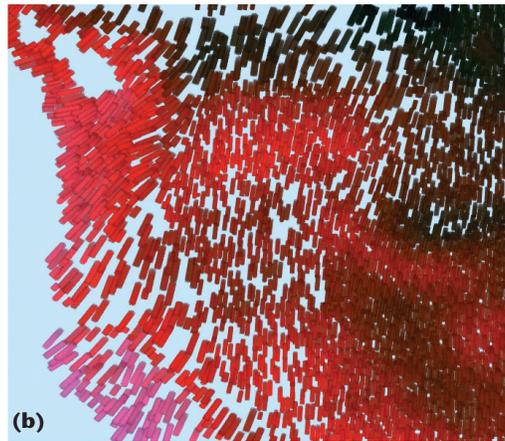
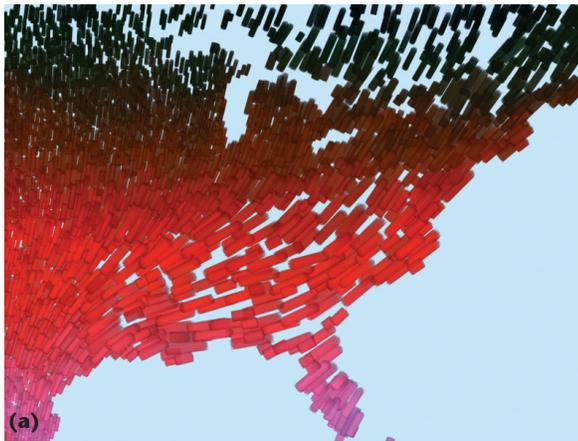
One final point of interest is that our results show that computer-generated images can be seen as highly artistic. Those who preferred realism felt the nonphotorealistic renderings were artistic. People who preferred abstractionism felt the painterly visualizations were artistic. We were initially concerned that viewers might believe a computer-generated image could never be seen as art. Our results suggest that this isn't true.

### Real-world visualizations

To tie these ideas together, we present a final painterly visualization from the application testbed we've used throughout much of this article: a dataset of monthly environmental and weather conditions collected and recorded by the Intergovernmental Panel on Climate Change. This dataset contains mean monthly surface climate readings in half-degree latitude and longitude steps for the years 1961 through 1990 (for example, readings for January averaged over the years 1961 through 1990, readings for February averaged over the years 1961 through 1990, and so on).

We visualize temperature, wind speed, pressure, and precipitation with a data-feature mapping  $M$  that assigns brush stroke color, coverage, size, and orientation, respectively. We show temperature with colors selected uniformly from a perceptually balanced color path that runs from dark blues and greens (for cold temperatures) to bright pinks (for hot temperatures). We show wind speed with coverage (coverage is the amount of an element's spatial region covered by its brush strokes). Coverages range exponentially from very small (for little or no wind) to full (for strong winds). We show pressure with sizes ranging from small (for low pressure) to large (for high pressure). Finally, we show precipitation by orientations ranging from 0 degrees or upright (for no precipitation) to 90 degrees or flat (for heavy precipitation).

Figure 6a shows a visualization of data for February across the eastern US. Figure 6b shows data for the same



6 Painterly visualization of weather conditions over the continental US: (a) weather conditions for February over the eastern US and (b) weather conditions for February over the west coast.

month along the west coast. Although it's unlikely that anyone might mistake these images for real Impressionist paintings, we feel these images contain important aesthetic qualities that make them stand out from traditional visualizations. Color and texture patterns representing different weather phenomena can be seen within these images. For example, Figure 6a shows the expected cold to hot temperature gradient (dark blue strokes to bright pink strokes) running north to south, light rain and strong winds (upright strokes that fully cover the background canvas) in the center of the country, and heavy rain and weak winds (tilted strokes with low coverage) in the south and northeast of the Great Lakes. Figure 6b highlights the warmer temperatures and heavy rainfall (tilted pink and red strokes) typically found in the Pacific Northwest around Seattle and Olympia during the winter months.

The ideas discussed in this article represent the first steps in our investigation of the roles of perception and aesthetics in scientific visualization. Our ongoing efforts include new experiments to study how changing an image along an emotional dimension affects a viewer. For example, we're testing visualizations with sharp discontinuities in the brush stroke properties (representing an increase in visual complexity), and we're also studying how an initial explanation of the visualizations changes a viewer's rankings (representing an increase in meaning.) Results from these experiments will offer further evidence on how variations in an image and its context can affect a viewer's aesthetic judgments.

We're also pursuing other avenues of investigation. For example, we're searching for new brush stroke properties that might let us increase the expressiveness of our nonphotorealistic visualizations. We're discussing how the dynamic properties of a computer screen can be used to animate our paintings, hopefully in ways that draw attention to important information in the dataset. We're optimistic that these ideas will promote further interest in the relationship between effectiveness and aesthetics in scientific visualization. ■

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