The Utility of Beautiful Visualizations

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Abstract: Geovisualizations provide a means to inspect large complex multivariate datasets for information that would not otherwise be available with a tabular view or summary statistics alone. Aesthetically appealing visualizations can elicit prolonged exploration and encourage discovery. Creating data geovisualizations that are effective and beautiful is an important yet difficult challenge. Here we present a tool for rendering geovisualizations of continuous spatial data using impressionist painterly techniques. The techniques, which have been tested in controlled studies, vary the visual properties (e.g., hue, size, and tilt) of brush strokes to represent multiple data attributes simultaneously in each location. To demonstrate this technique, we render two examples: 1) weather data attributes (e.g., temperature, windspeed, atmospheric pressure) from the NOAA Global Forecast System and 2) fragile state indices as assessed by the Foreign Policy Magazine. These examples demonstrate how open source geospatial visualizations can harness aesthetics to enhance visual communication and viewer engagement.

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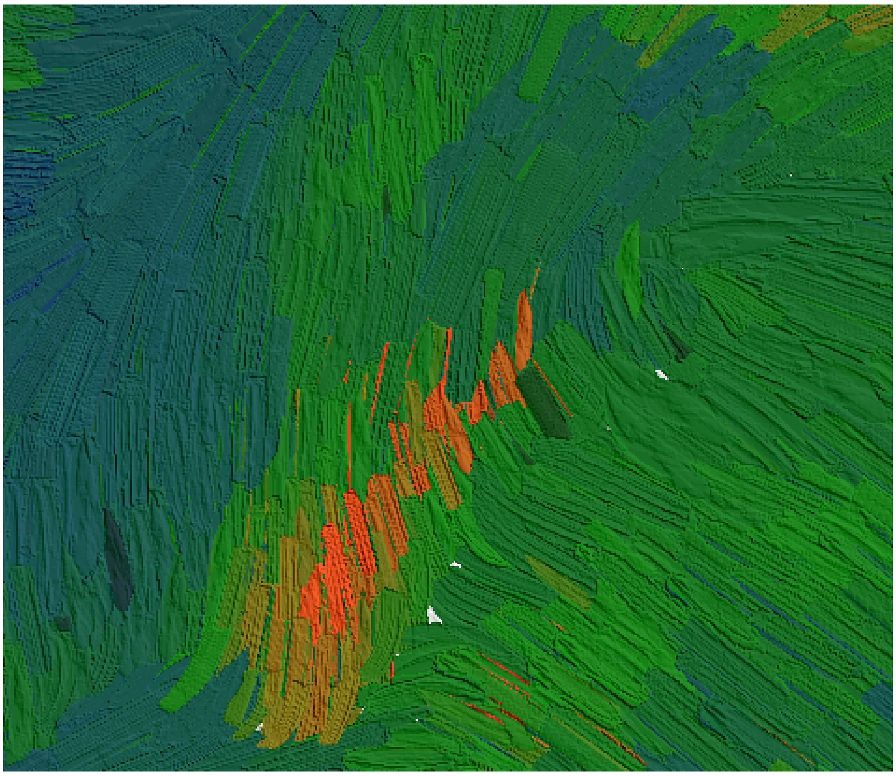


Figure 1: Painterly geovisualization of atmospheric data.

1. Introduction

As geospatial data collection and storage capabilities continue to grow, innovative visualization techniques are needed to support the extraction of information from datasets. Visualizations, graphical representations of data, can provide valuable insights into the datasets they represent. The term, visualization, is also used to refer to the process of converting raw data into images. Often, each of the data elements in a large data set has multiple attributes. For example, scientists studying the climatic El Niño data collect wind data, humidity, air temperature, sea surface temperature, latitude, and longitude, and other variables at buoys spanning the Pacific Ocean. Thus, in the resulting dataset an element represents a buoy and each element has more than six attributes. To visualize an m-dimensional data set of n elements, a set of visual features, V = $\{V_1, ..., V_m\}$ can be chosen to represent the data's set of attributes, A = $\{A_1, ..., A_m\}$. Examples of visual features include hue, texture, flicker, size, orientation, curvature, and regularity.

One approach to visualizing large multivariate datasets is glyph-based visualization Borgo et al. 2013. Glyphs are small visual elements, whose individual visual properties (color, shape, size, etc.) can be varied separately to represent the variations in the data attributes. Since glyphs can display several visual features at once, they can convey information about several attributes simultaneously. Studying human perception provides insights into how to use glyphs to best harness the human visual system. Human vision operates in two distinct modes Julesz 1984. First, preattentive vision is instantaneous and independent of the number of elements in the display and covers a large visual field. Preattentive vision includes the psychology concept called orienting, which refers to a reflexive direction of attention in response to a salient local stimulus, such as the sudden appearance of a new object Healey and Enns 2012. Second, attentive vision searches serially by focal attention and is limited to a small spatial aperture.

Attentive vision requires engagement, which means a viewer's attention is held for a longer period of time at each spatial locatio Healey and Enns 2012.

Geovisualizations that are designed for human perceptive strengths *and* aesthetic appeal may improve engagement and help to direct the viewer to key components of the representation, as the brush strokes in painterly visualization in Fig. 1 draw the viewer's eyes down and to the left conveying the dominant motion of the underlying flow data. Techniques from the realm of the visual arts can inform design decisions in geovisualization. Geovisualization can benefit from a long-standing interest in the computer graphics community in developing rendering algorithms for artistic techniques.

The computer graphics fields of non-photorealistic rendering (NPR) integrates artist techniques into graphics renderings with early examples simulating various artistic media, including pen-and-ink drawing, watercolor, charchoal, oil painting, and colored pencil. Strothotte and Schlechtweg 2002 provides a comprehensive review of this field. Ideas from NPR inspired non-photorealistic layered visualizations of brain matter Laidlaw et al. 1998 and airfoil wind flow patterns Kirby et al. 1999, as well as stippling Lu et al. 2002 and boundary enhancement Rheingans and Ebert 2001 for medical volume visualizations. Others began to bring NPR into geovisualization with natural patterns on agricultural maps Interrante 2000 and bus-maps with Mondrian painting designs Skog et al. 2003. Recent work developed a direct-manipulation user interface to enable artists to design new data geovisualizations Schroeder and Keefe 2016. The resulting geovisualizations exhibit a masterful use of color. Also, web designers are developing appealing geovisualizations that consume global datasets[1] and near real-time weather data Beccario 2014.

In this paper, we look at an example of aesthetic geovisualization that is inspired by Impressionist painter, Vincent Van Gogh. Visual features of brush-stroke glyphs portray multiple data attributes at each position. Tateosian et al. 2007 describes the design and algorithms of these techniques. The painting algorithm randomly selects unpainted data positions for brush strokes until the desired coverage is reached and assigns visual features, stroke color, size, and tilt, to represent the underlying data at the center of its assigned position.

Tateosian et al. 2007 developed three distinct visualization styles based on properties of aesthetics. The examples in this paper feature *visual complexity*, a style resembling the later works of Vincent van Gogh. In work by Kozik et al. accepted the three painterly styles, along with a standard visualization employing rectangular glyphs on a regular grid were shown to participants in a set of experiments. A first experiment found that visual complexity was comparable to standard glyphs and superior to the other painterly styles for memorability. A second experiment tested participants' ability to report the prevalence of the color blue (representing a single weather condition) within each visualization. For this task, visual complexity was superior to glyphs and the other impressionist styles.

The implementation of the visualization techniques demonstrated here are available in a C++/OpenGL painterly visualization code base[2]. The visual complexity style uses a fast paint texture NPR technique Hertzmann 2002 to simulate a painted surface by assigning height values to texture maps on the strokes and calculating the lighting based on those values. The user can assign six data attributes to six visual features. The first four features are the hue, luminance, size, and tilt of brush strokes. The last two are termed *contrast* and *proportion.* Contrast changes the tilt and luminance of a subset of strokes in a region. In Fig. 2a a few dark green strokes at a 45°tilt contrast the field of light green tilted at 135°. The tilt of the contrast

[1]https://www.jasondavies.com/

[2]NPV code available at https://github.com/lgtateos/pittore-rep

(a) Contrast strokes (b) Proportion (long+narrow) (c) Proportion (short+wide)

Figure 2: Visual features, *contrast* and *proportion*, extend the standard visual lexicon.

strokes is rotated by 90 degrees and the luminance is shifted down to create noticeably darker strokes perpendicular to the dominant stroke direction in that area. The proportion attribute uses three bins, high, very high, and the rest. The standard proportion for strokes is 1:4 (one wide to four long). When the value of the attribute assigned to proportion exceeds a very high threshold, the stroke length is exaggerated and the width is narrowed, changing the proportion to 1:25. In Fig. 2b, light pink long narrow strokes are centered on values which fall above the threshold. High, but not very high, are represented with wide short strokes (7:5 ratio). Peach-colored strokes in the upper right corner and orange strokes in the upper left corner of Fig. 2c are centered on high values. The direction of the stroke is still apparent because of the simulated bristle texture. Visual complexity style also implements b-splines for stroke curvature that can be used for flow visualization (Fig. 1).

Computational geometry techniques are used to segment the data into regions based on the set of underlying data values at each point. Each region is painted by first randomly selecting an unpainted pixel, sizing and tilting the stroke based on underlying data, and then checking the segment boundaries and the overlap with existing strokes. If the latter are within acceptable thresholds, the stroke is placed there. This continues until the desired segment coverage is met. Tateosian et al. 2007 describes the segmenting and painting algorithms in detail. This standalone code uses a Mercator projection for stroke placement as it has not yet been integrated with existing geographic libraries. Examples of practical applications for painterly and ideas for integrating aesthetics into geovisualization tools to increase expressiveness are presented in the following section.

2. Painterly geovisualizations

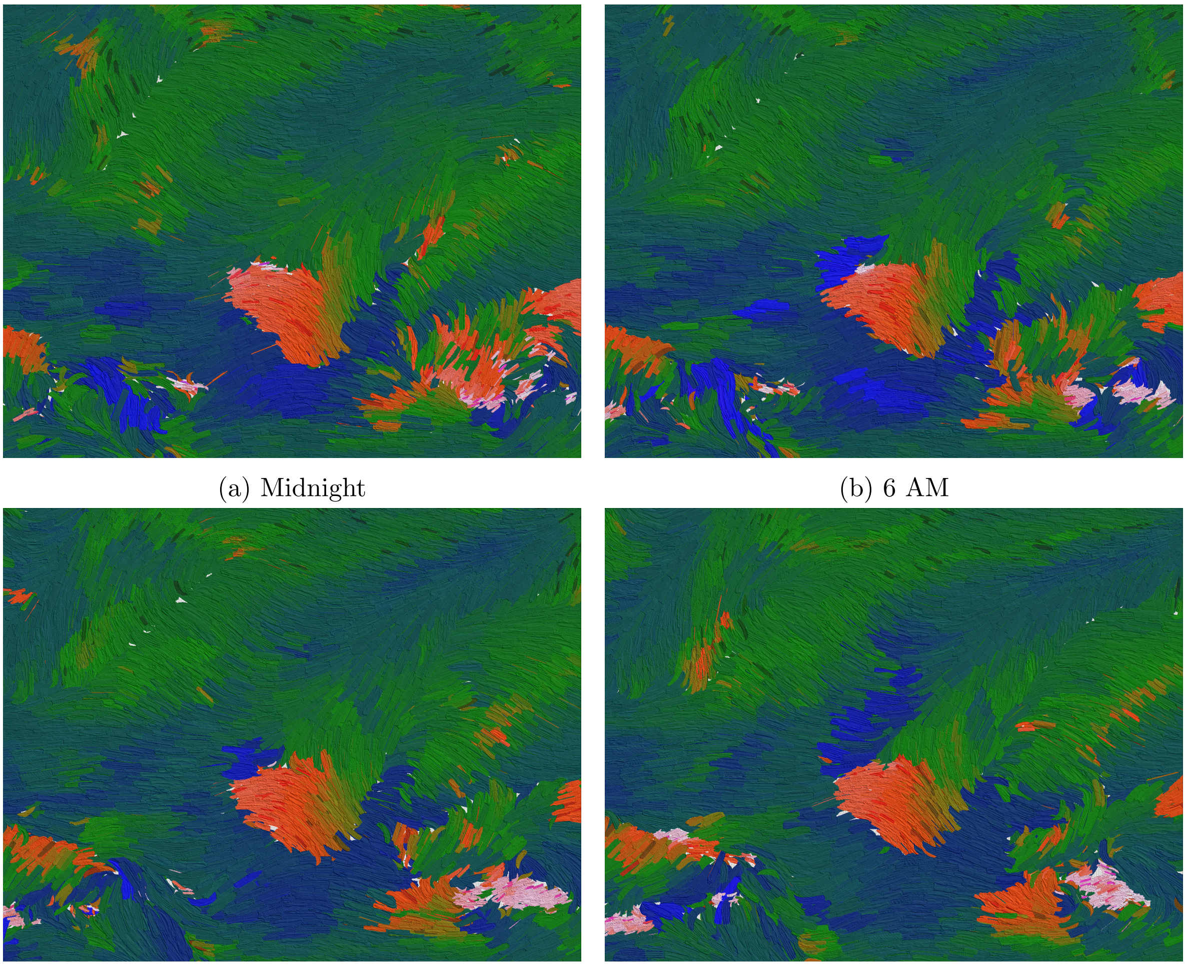
Here we test the visual complexity style geovisualizations on large multivariate datasets within two domain applications. The first application, atmospheric data, is a spatially continuous dataset, sampled at regular intervals. The second domain, fragile states indices, portrays polygonal data, with continuous attributes assigned to each country, instead of regular grid cells.

2.1. Weather data time series

The University Corporation for Atmospheric Research (UCAR) hosts massive volumes of atmospheric data. These datasets enable atmospheric scientists to study processes that can lead to hurricanes or cyclones, such as El Niño and African Easterly Waves, problems that entail inspecting combinations of attributes such as wind direction and water surface temperature. We extracted NOAA Global Forecast System data collected at 0.25° resolution and six-hour intervals[3]. Six of the available attributes were selected to make up these datasets, temperature,

[3] See http://thredds.ucar.edu/ for Global Forecast System data

geopotential height, and pressure at maximum wind level, precipitable water, and finally, u and v components of wind at maximum wind level, which were combined to calculate wind direction.



(a) Midnight

(b) 6 AM

(c) Noon

(d) 6 PM

Figure 3: Painterly geovisualization of atmospheric data mapping: temperature → stroke hue, geopotential height → stroke size, wind direction → stroke tilt, pressure → contrast strokes, cloud water → stroke proportion.

Figs. 3a-3d show four time-steps from the same day (May 25, 2017), six hours apart starting at midnight. Temperature, geopotential height, and wind direction are represented with stroke hue (blue-green-brown-orange-pink), size (small to large), and tilt. Pressure and cloud water are represented with contrast strokes and stroke proportion. Studying these images, we see several distinctive features: shifting turbulence near the lower right corner, warmer temperatures with a high pressure system appearing in the upper left at 6pm, and lower geopotential height in the north than the south all day.

2.2. Fragile state index

The Foreign Policy Magazine releases an annual Fragile States Index, rating each country on a number of measures to model the country's fragility or likelihood to become a failed state. A committee of economists assigns values for indices on a scale from 1 for good to 10 for poor. Twelve factors are evaluated and summed to compute a total which is used to rank order 178 countries in terms of fragility. Fig. 4 visualizes the overall state fragility ranking and four of the ranking factors, including poverty and economic decline, protection of human rights, demographic pressures such as food scarcity and population growth, and state legitimacy as a measure of corruption, government performance, and the electoral process. We retrieved the data from the Foreign Policy Magazine web site[4].

The rank ordering in Fig. 4 is mapped to the majority color of the brush strokes, which varies from low to high on the perceptually balanced continuous blue-green-brown-orange-pink color ramp, e.g., pink central African countries are highly fragile, while blue Canada has low fragility. poverty and economic decline is mapped to stroke size, e.g., Guinea in northwest Africa has large strokes due to the high poverty rates there. In contrast, states like Norway have very small strokes to represent their very low poverty rates. Protection of human rights is mapped to stroke tilt, with the vertical stroke in central Africa reflecting human rights concerns and the horizontal strokes in New Zealand on the other end of the spectrum. Demographic pressure is mapped to contrast strokes. Strokes that contrast in luminance and tilt to the color and tilt assigned for that state represent those above a threshold. For example, China and Brazil have high population growth pressures while Australia doesn't, since the strokes are monotone and all tilt in the same direction. State legitimacy is mapped to stroke proportion, which overrides the standard proportionality (1:4) of the strokes. When corruption values are very high the strokes are long and narrow relative to the standard proportion. For example, North Korea and the Congo are painted with a number of long narrow strokes, since they have poor state legitimacy ratings. Corruption in Egypt falls within the high (but not very high) range with short wide strokes visible there. The tool provides interactive zoom and pan with the mouse for users to inspect the visualization more closely.

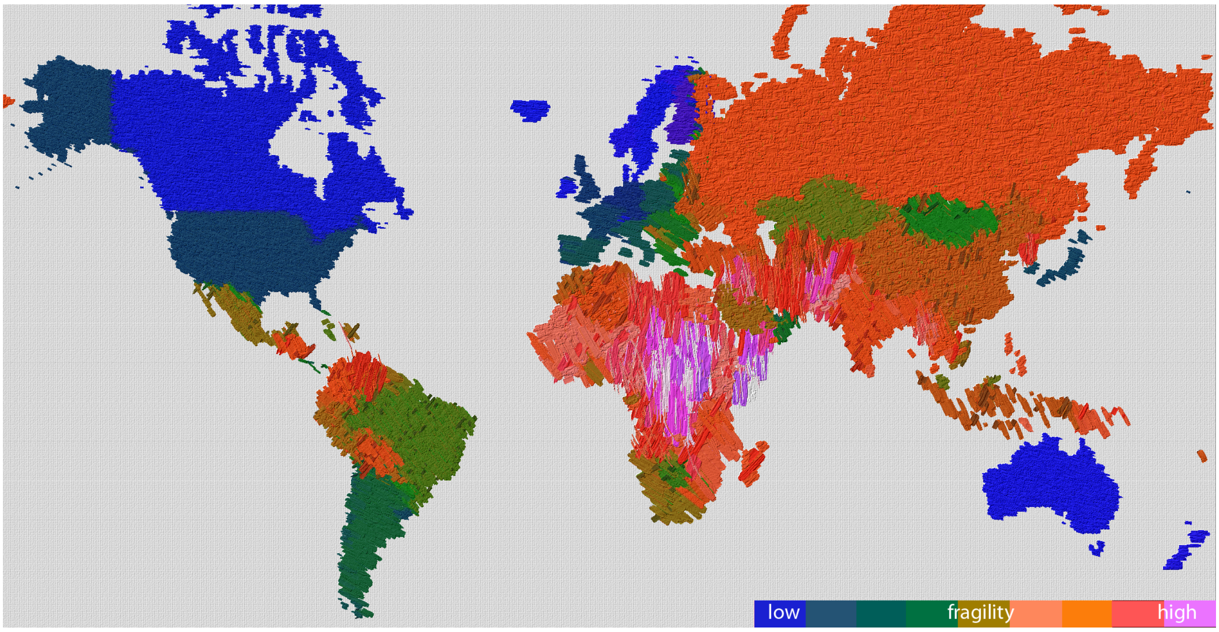


Figure 4: Painterly geovisualization of the 2016 state fragility index by the Foreign Policy magazine (FSI Data, 2017). Mapping fragility → stroke hue, poverty and economic performance → stroke size, human rights to stroke tilt, contrast strokes → demographic pressure, stroke proportion → state legitimacy (corruption).

3. Conclusions

The glyph-based approach enables multiple attributes to be visualized in a single location, so that interactions may be determined and appealing geovisualizations such as the visual complexity examples shown here may engage viewers and result in new discoveries. GIS platforms

[4]http://foreignpolicy.com/fragile-states-index-2016-brexit-syria-refugee-europe-anti-migrant-boko-haram/

(both open source and proprietary) that can support artistic geovisualizations are almost non-existent. Integrating stand-alone tools such as this into existing open source GIS systems will further enhance the visualizations. Established geospatial frameworks can provide the capability to apply different projections, to overlay the images with other spatial layers for geospatial context, generate legends, provide graphical user interfaces to guide users and add picking for inspecting individual elements. At the same time, geovisualization developers may be able to develop tools that make it easier to develop more expressive and engaging visualizations by leveraging the creativity and visual salience of artistic techniques.

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