Perception-Driven Techniques for the Effective Visualization of Large Volume Data

So Many Parameters, So Little Time…. Guiding Users To Obtain Better Visualizations

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The Conceptual Data Visualization Pipeline

- Parameterization of all pipeline components is essential
  - allows tuning and optimization of the visual transform given the data and the user
  - shall look at each pipeline component and then join them
What We Will NOT Talk About

• We shall not consider data arrangements here
  • such as grids, lattices, spatial dimensions, etc.
  • assume sampling is not an issue
  • assume interpolation and errors are understood
  • further assume that the methods generalize to higher spatial dimensions

• There is still plenty to if stuff to worry about ☺
Topic 1: The Data and Their Parameterization

• Data may come as:
  • scalar data (densities)
  • multi-valued data (multi-variate)
  • vectors (vector fields)
  • and others
• Data parameterization = data characterization
• How can data be characterized?
  • their features
• What are these features?
  • this is the hard part ☻
The Raw Data

- Scalar density fields (topic of this tutorial)
  - Medical
  - Scientific
  - Multi-modal or multi-variate (example: T1/T2 MRI)
- Vector fields
- Tensor fields
  - MRI DTI

Direct Visualization Of Scalar Densities

- Contrast: the role of color
  - Variations in brightness (grey levels) encode local contrast well
  - But the range of distinguishable grey levels is small (~100)
  - Grey levels are good for local but not for global contrast

[Ware 04]
Direct Visualization Of Scalar Densities

• Color for highlighting
  • color is effective in guiding viewer attention to salient features
  ➔ in particular, vividness (saturation) is important here

[Wang 08b]

Direct Visualization Of Scalar Densities

• Aesthetics
  • color can make a display more cheerful and pleasing
  • aesthetic design can also reduce stress in problem solving tasks
  • objects considered beautiful stimulate different areas in the brain than those considered unattractive [Kawabata 04]
  ➔ this motivates the use of harmonized color schemes

[Wang 08a]
Direct Visualization Of Scalar Densities

- At this point, we have done analysis only on a per pixel-basis
  - may have involved global scene analysis (e.g., for highlighting)
- One may map scalar densities to
  - other scalar densities: windowing of interesting ranges
  - colors
  - transparencies
- This mapping may be driven by functions of
  - importance
  - aesthetics
  - certainty
  - and others

Direct Visualization Of Scalar Densities

- Essentially we get a 1-D transfer function: density $\rightarrow$ color
Direct Visualization Of Scalar Densities

• Essentially we get a 1-D transfer function: density $\rightarrow$ color

• Let us now look at more complex analyses
  • creating new, derived data

Accentuate Events In The Data

• Flat, uniform regions are not particularly interesting
• We are interested in events and critical points $\rightarrow$ the features
  • thus, accentuate discontinuities and variations in the data
• Visually convey these events by graphical techniques
• Can still use transfer functions for this
  • their complexity grows with the complexity of the event descriptor

• Distinguish between:
  • analytic feature detection via derivatives and moments
  • analytic feature detection looking for topology changes
  • statistical feature detection calculating histograms and variance
Boundaries in volume create arches in (value, gradient) domain [Kindlmann 98]

These arches can guide placement of opacity to emphasize material interfaces [Kniss 01]
Three-Dimensional Transfer Function

Boundaries can be described in terms of:
- maximum in 1st derivative
- zero-crossing in 2nd derivative

Semi-automatic classification possible in clean data

Transfer Function for Perceptual Enhancement

Add in additional properties, such as curvature

Curvature: how the change in surface position changes surface normal (n)
- principal curvature features (κ₁, κ₂) form the transfer function domain
- curvatures enable surface surface enhancement, better control over silhouettes
- convolution used to compute 1st and 2nd derivatives

[Kindlmann 03]
Effects Of Curvature Enhancement

- silhouettes
- ridges+
- valleys
- ridges+
- valleys+
- silhouettes

Analysis Of Level Set Topology

- Level-Set = Iso-contour
  - contours of equal interpolated scalar density

![](image1.png)

![image2.png]
Analysis Of Level Set Topology

- Level-Set = Iso-contour
  - contours of equal interpolated scalar density

Contour tree
Reeb Graph

Statistical Features

- What to do when there are no concrete topological events or boundaries, yet the density field is not uniform?
  - simple example found in nature: smoke
- Assess the spectrum of density variations
  - density histograms
- Apply a descriptor rooted in human perception
  - humans most sensitive to 1st and 2nd spatial derivatives
  - already used in the transfer function context
  - now use in a statistical context

[Pascucci 03]
Density Global Histogram

Density Local Histogram

- Density signatures in local histograms at hierarchy of window sizes
- Detect density statistics at multiple levels of scales
- Representation to capture the essence of an object.

this and following slides: [Nam 08]
SIFT (Scale Invariant Feature Transform)

- Gradient histogram of local neighborhood
- Highly expressive of a local neighborhood’s salient dynamics
- Invariant to scale, translation and rotation

Algorithm
- the detection of critical points (the keypoints) in scale-space
- the encoding of these into keypoint descriptors

- Find keypoints
  - local extremas in a difference-of-Gaussians in multi-scale space
  - Discard low contrast keypoints
  - Filter out keypoints situated on edges

Pictures from Wikipedia.org
SIFT (Scale Invariant Feature Transform)

- Keypoint descriptor
  - the magnitude and orientation at each sample point around the keypoint location
  - weighted by a Gaussian function to achieve a certain level of smoothing.
  - aggregated into orientation histograms describing the neighborhood

3D SIFT

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\[ 8 \times (4 \times 4) = 128 \]
3D SIFT Descriptor

\[ (8 \times 8) \times (4 \times 4 \times 4) = 4096 \]
3D SIFT Descriptor
Cluster Analysis on Visual Contents

Feature Visualization in an Information Space

MDS (Multi-Dimensional Scaling) - Flatten N-D data into 2-D display while preserving the inter-distance between dataset
MDS Analysis: Categorization

1. Categorize different groups of flows
2. Distinguish different features within same category

Categorization Of 3D Flows

- 5 frames extracted from each series
- Features
  - Global histogram
  - Local histogram
  - 3D SIFT
Conclusion: Data Features

• The more the data characteristics are understood the more specific the features will be (in most cases)
  • opposite extremes: feature templates vs. neural networks
  • others are somewhere in between
• Feature specification can be embedded in a data exploration process
  • neural networks require users to provide feature examples in the dataset
  • these may then be re-used in later visualizations
**Topic 2: Visual Transform**

- Determines how features are expressed into visual manifestations = their visual appearance
- Features may control the rendering pipeline at various stages:
  - local color and opacity (mapping via transfer function)
  - scene composition (local sparseness, warping by lenses)
  - rendering style (lighting model, illustrative techniques)
  - iconic sprites (specific visual expression)

**Topic 2: Visual Transform**

- We can use transfer functions to maps feature parameters into visual transform parameters
  - what to do when parameter vector is large?
  - what to do when transfer function is complex?
- We have seen clustering/MDS as a way to visualize similar features
  - implicit parameterization is given by location in MDS cluster
- Can we make the parameterization more explicit?
  - detect parameter combinations sensitive to change
  - come up with templates given prior experiences
Example: Complex Transfer Function

A more elaborate value-gradient transfer function parameterization:

Typically, datasets typically deviate only modestly from this
• but they do so in complex ways
  → lots of tedious tweaking is required

[Rezk-Salama 06]

Parameter Aggregation

We can learn these small deviations by observing a few datasets
• encode the parameters into an N-D vector
• find the principal component of the vectors (the main Eigenvector)
• project all other vectors onto this Eigenvector
• the min and max then represent the min and max of the slider

[Rezk-Salama '06]
Transfer Function Simplification

Transformed aggregation enables transfer function simplification from N-D to 1-D

- works here since in CT usually only small deviations exist
- but these small deviations require complex interactions in the transfer function domain

[Rezk-Salama '06]

Topic 3: The User, The Human Visual System

Visual cortex breaks input up into different aspects:
- color, shape, motion, depth
Visual Saliency

- Notion of visual importance

Visual Saliency

- Notion of visual importance
- Visual transform of data features to direct a viewer's attention
  - shape (edges, silhouettes)
  - surface (curvatures, suggestive contours)
  - size
  - intensity and color
  - texture
Visual Saliency

- Notion of visual importance
- Visual transform of data features to direct a viewer’s attention
  - shape (edges, silhouettes)
  - surface (curvatures, suggestive contours)
  - size
  - intensity and color
  - texture
- Enhancement / suppression makes this more effective
  - opacity controls presence
  - rendering style and texture control expression and appearance
  - illumination controls shading
  - intensity and color control attention (by highlighting)
  - caricature controls shape
  - but these influences are typically mixed (and not exclusive)

Halos

Bruckner et al., 2006
Wenger et al., 2006
Two Levels Of Abstraction

- Low-level abstraction:
  - concerned with how objects are represented
  - stylized depiction: silhouettes, contours, pen+ink, stippling, hatching, etc.

- High-level abstraction
  - deal with what should be visible and recognizable and at what level of detail
  - this should be importance-driven, that is, the current visualization goal controls feature rendering style and visibility
Mixing Rendering Styles

- First, classify the scene:
  - **Focus Objects (FO):** objects in the center of interest are emphasized in a particular way
  - **Near Focus Objects (NFO):** important objects for the understanding of the functional interrelation or spatial location.
  - **Context Objects (CO):** all other objects (rendered e.g., as silhouettes)
  - **Container Objects (CAO):** one object that contains all other objects.
- Render these in a certain order to ensure visual consistency

Tietjen et al., 2005

Attention

- The cognitive process of selectively concentrating on one thing while ignoring other things
  - detecting features in visual clutter (CAPTCHA, next slide)
  - detecting coherent speech in noisy environments (cocktail party effect)
  - ignore features while concentrating on others (recall gorilla)
  - can also have divided attention (example: cell phone + driving)
  - heavily studied in psychology and neuroscience
  - closely tied to perception
Attention

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  • detecting features in visual clutter (CAPTCHA, next slide)
  • detecting coherent speech in noisy environments (cocktail party effect)
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• Attention theory is important for visualization as well
  • in contrast to computer vision, WE design/create the scene
  • this design guides the attention of the viewer
  • guidance determined by visualization goals

• Therefore it is important to understand mechanism of attention
Visual Recognition and Attention

- Two opposing theories:
  - Gestalt
  - Feature integration
- Gestalt theory
  - top-down approach
  - proposes that the operational principle of the brain is holistic, parallel, and analog, with self-organizing tendencies
  - important in user interface design (button grouping, etc)
- Feature integration theory
  - bottom-up approach
  - primary visual features are processed and represented with separate feature maps
  - these are later integrated in a saliency map that can be accessed in order to direct attention to the most conspicuous areas

Gestalt Theory: Confirming Examples

- Emergence
- Invariance
- Reification
- Multi-Stability
Gestalt Theory: Opposing Examples

• **Selective-Encoding:**
  • involving one to distinguish what is important in a problem and what is irrelevant (i.e., filtering)

• **Selective-Comparison:**
  • identifying information by finding a connection between acquired knowledge and experience

• **Selective-Combination:**
  • identifying a problem through understanding the different components and putting everything together.

Feature Integration Theory

• One of the most influential psychological models of human visual attention in recent years
• Two types of visual search mechanisms
  • Feature search
    • can be performed fast and pre-attentively for targets defined by primitive features (such as color, orientation, intensity, etc)
  • Conjunction search
    • serial search for targets defined by a conjunction of primitive features
    • much slower
    • requires conscious attention
  • Very promising technique for computer vision to detect partially occluded objects (SIFT)
What Does It Mean For Visualization?

• Feature integration theory:
  • justifies enhancement of features
  • exploit this to guide attention
  • relatively “easy” since it involves mostly local enhancements
  • notion of feature saliency is important

• Gestalt theory:
  • justifies omission of detail to save space
  • viewers assume continuity of occluded lines
  • underlies ghosting techniques (mental feature completion)
  • silhouettes and contours for context objects
  • many techniques used now in illustrative rendering
  • recall also optical illusions
Some design rules exist, but combinations are often untested

Also consider
- user background (education, age, gender, profession, attitude, etc)
- underlying task and application (medical, business, science, etc)
- computational resources and level of interactivity sought
- other factors

User studies can reveal this insight
- they allow, in some sense, a parameterization of the user

An effective and efficient means for user studies is **conjoint analysis**
- allows parameters to be tested in a conjoint fashion, via pair-wised comparison tests (or task-based tests)
- subsequent statistical analysis then separates the sensitivities of these parameters
Sample Testing Scenario

- Which color transfer function shows more detail?

Putting Conjoint Analysis to the Test

- Performed a user study on a multi-parametric visualization scenario
- On a set of 2700 images of engine blocks, we varied:
  - color transfer function (3)
  - rendering mode (5)
  - viewpoint (6)
  - image resolution (2)
  - ray step size (3)
  - background (5)
- Tested
  - 786 respondents
  - 20 pair-wise tests each

[Giesen '07]
User Study Results

- Top 10 (detail / aesthetics):

- Flop 10 (detail / aesthetics):

Wrap-Up

- Define the features that best characterize your visualization task
- Devise a suitable feature retrieval method
- Find a suitable mapping of these to salient visual representations
- Confirm and tune via user studies
References (1)


References (2)

- [Nam 08] J. Nam, M. Maurer, K. Mueller, "High-Dimensional Feature Descriptors to Characterize Volumetric Data," 2nd Workshop on Knowledge-Assisted Visualization (KAV), (to be presented), Columbus, OH, October, 2008
References (3)


More and Up-To-Date Information

- Visit http://vis.cs.ucdavis.edu/~wangcha/vis08-tutorial.htm

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