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

VisWeek 08
VIS • INFOVIS • VAST

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

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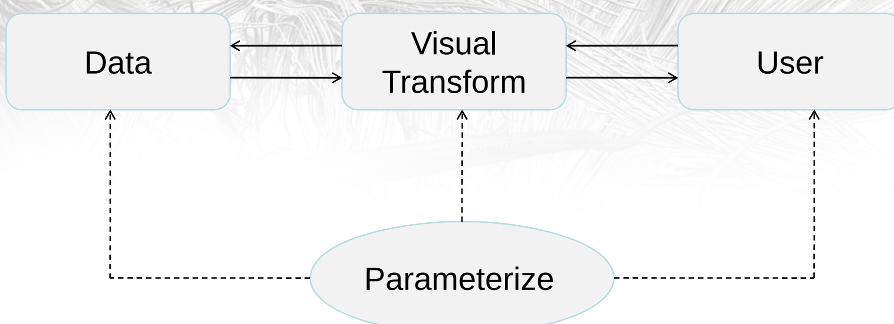
The Conceptual Data Visualization Pipeline



- 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

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?

Topic 1: The Data and Their Parameterization

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- Data parameterization = data characterization
- How can data be characterized?
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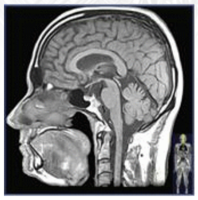
- What are these features?

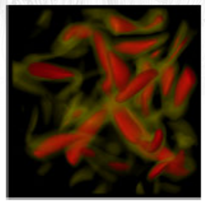
  - this is the hard part ☺

The Raw Data

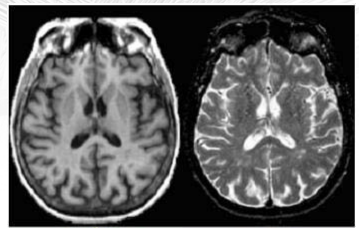
- Scalar density fields (topic of this tutorial)



medical



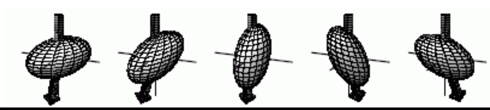
scientific



multi-modal or multi-variate (example: T1/T2 MRI)

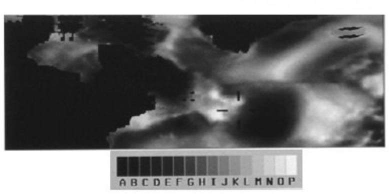
- Vector fields

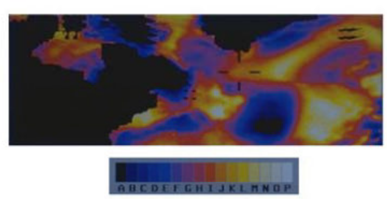
- Tensor fields
  - MRI DTI



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 <u>local</u> but not for <u>global</u> contrast





[Ware 04]

Direct Visualization Of Scalar Densities

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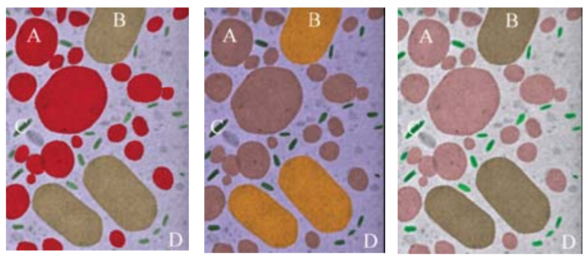
- Color for highlighting
  - color is effective in guiding viewer attention to salient features
  - → in particular, vividness (saturation) is important here



[Wang 08b]

Direct Visualization Of Scalar Densities

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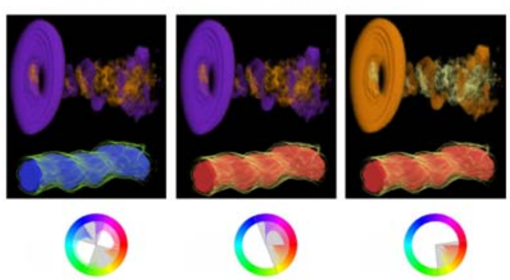
- Aesthetics
  - color can make a display more cheerful and pleasing
  - aesthetic design can also reduce stress in problem solving tasks
  - objects considered beautiful stimulate different areas in the brain than those considered unattractive [Kawabata 04]
  - → this motivates the use of harmonized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



non-harmonic T-harmonic V-harmonic

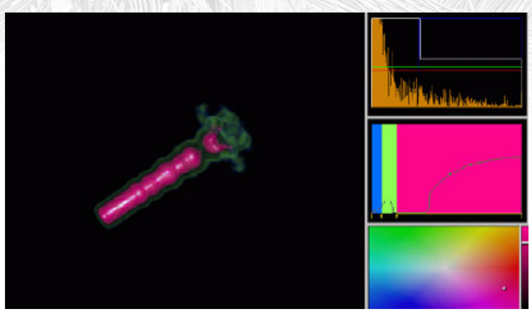
[Wang 08a]

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→ color



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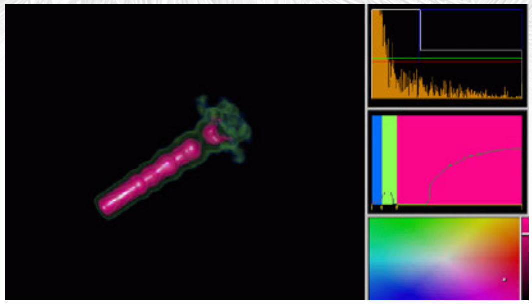
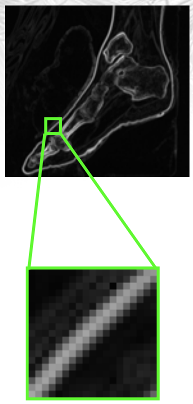


- Let us now look at more complex analyses
  - creating new, derived data

Accentuate Events In The Data

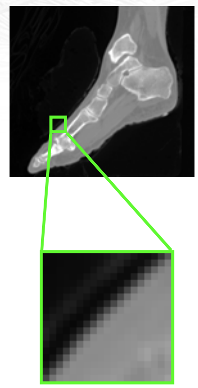
- Flat, uniform regions are not particularly interesting
- We are interested in events and critical points → the features
  - thus, accentuate discontinuities and variations in the data
- Visually convey these events by graphical techniques
- Can still use transfer functions for this
  - their complexity 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

Derivatives

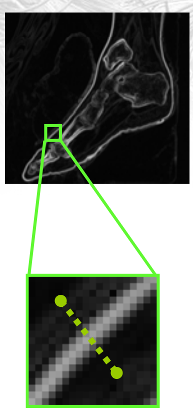


gradient magnitude

data (CT) value



Derivatives: Two-Dimensional Transfer Function



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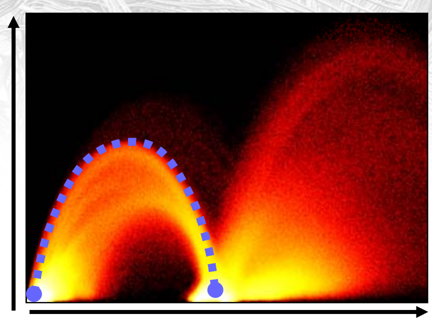
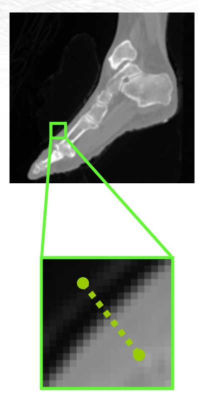


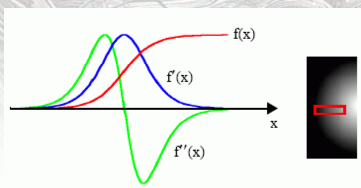
Boundaries in volume create arches in (value, gradient) domain [Kindlmann 98]

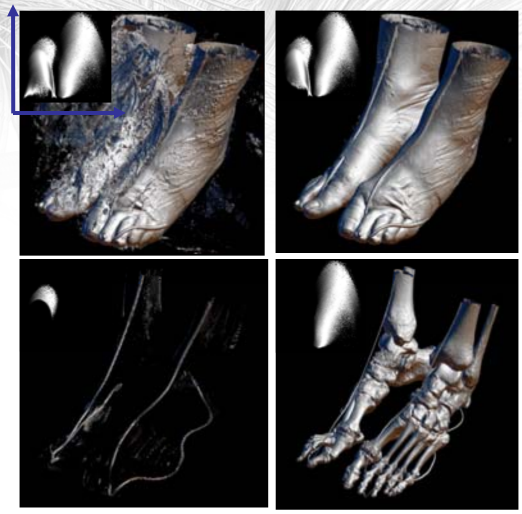
These arches can guide placement of opacity to emphasize material interfaces [Kniss 01]

data (CT) value



Three-Dimensional Transfer Function





Boundaries can be described in terms of:

- maximum in 1st derivative
- zero-crossing in 2nd derivative

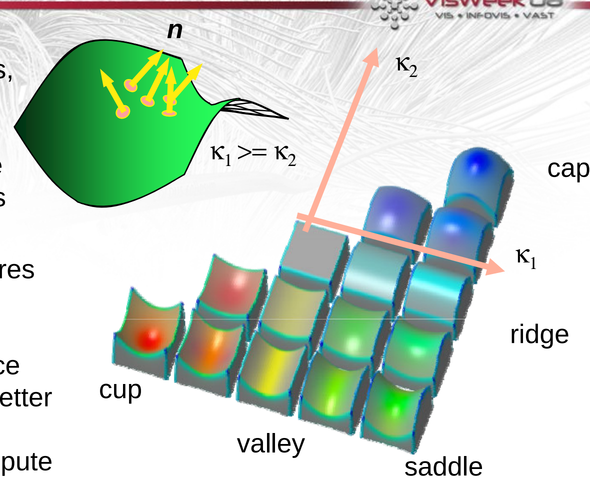
Semi-automatic classification possible in clean data

Transfer Function for Perceptual Enhancement

Add in additional properties, such as curvature

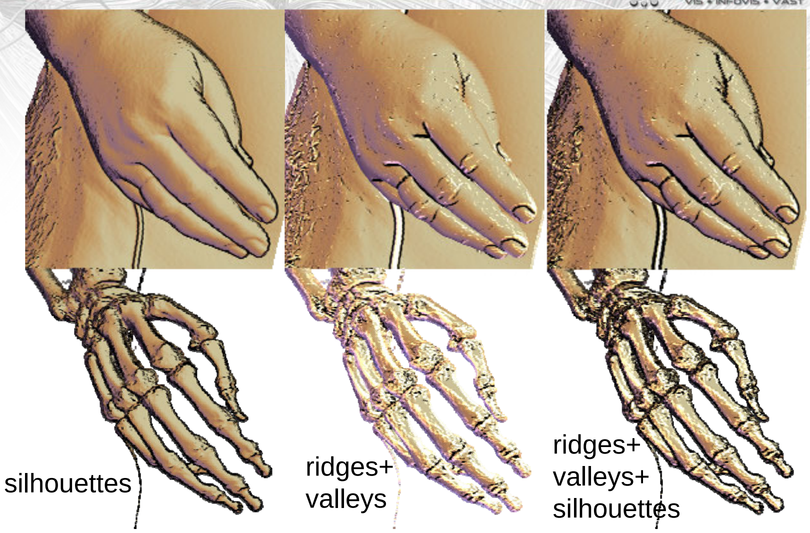
Curvature: how the change in surface position changes surface normal (***n***)

- principal curvature features (κ_1, κ_2) form the transfer function domain
- curvatures enable surface surface enhancement, better control over silhouettes
- convolution used to compute 1st and 2nd derivatives



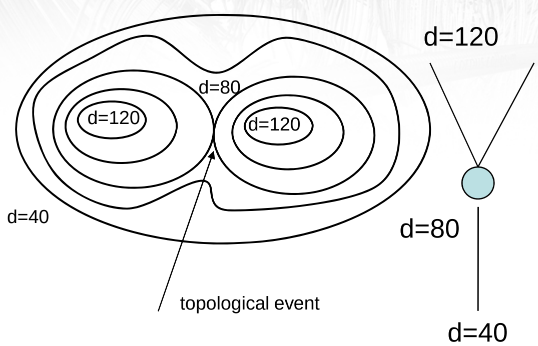
[Kindlmann 03]

Effects Of Curvature Enhancement



Analysis Of Level Set Topology

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



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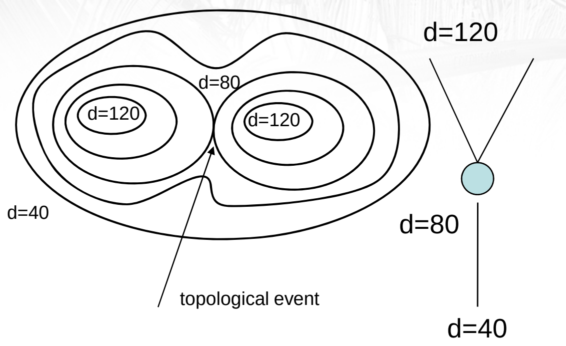
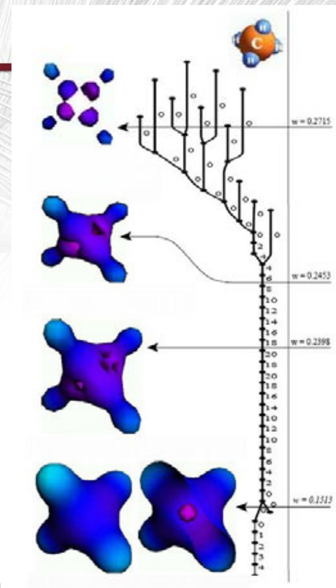


Contour tree
Reeb Graph

[Pascucci 03]



Statistical Features

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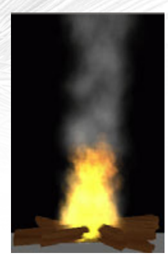
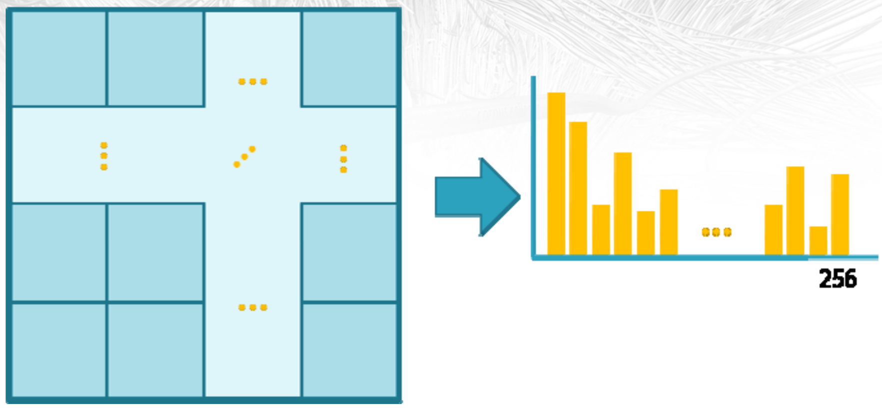
- What to do when there are no concrete topological events or boundaries, yet the density field is not uniform?
  - simple example found in nature: smoke
- Assess the spectrum of density variations
  - density histograms
- Apply a descriptor rooted in human perception
  - humans most sensitive to 1st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



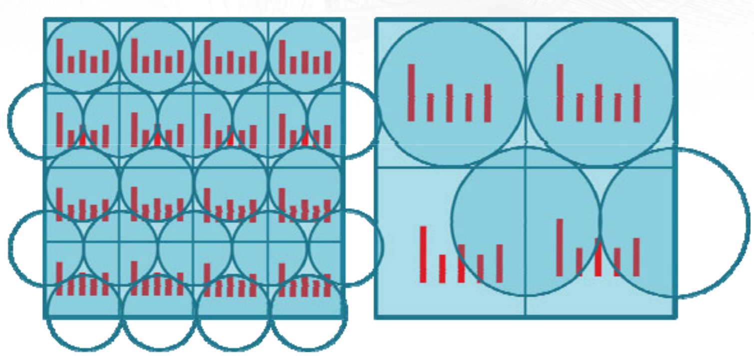
Density Global Histogram



this and following slides: [Nam 08]

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.



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*

SIFT [Lowe 04]

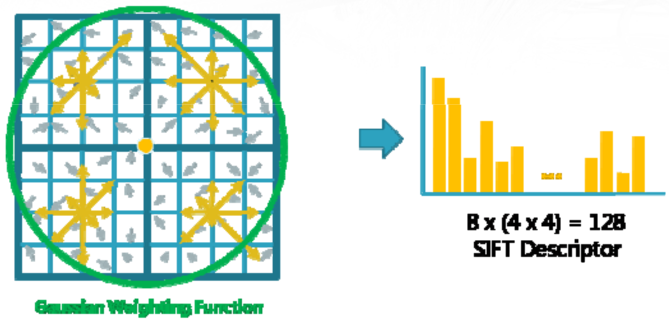
SIFT (Scale Invariant Feature Transform)

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

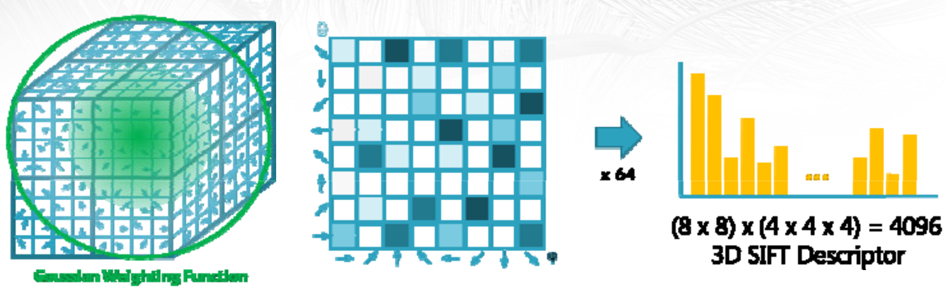
- Pictures from Wikepedia.org

SIFT (Scale Invariant Feature Transform)

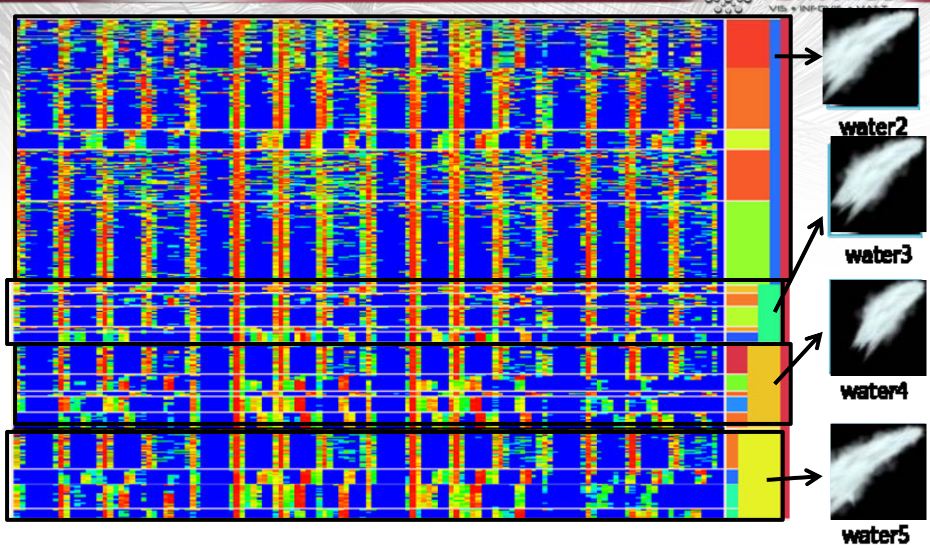
- Keypoint descriptor
  - the magnitude and orientation at each sample point around the keypoint location
  - weighted by a Gaussian function to achieve a certain level of smoothing.
  - aggregated into orientation histograms describing the neighborhood



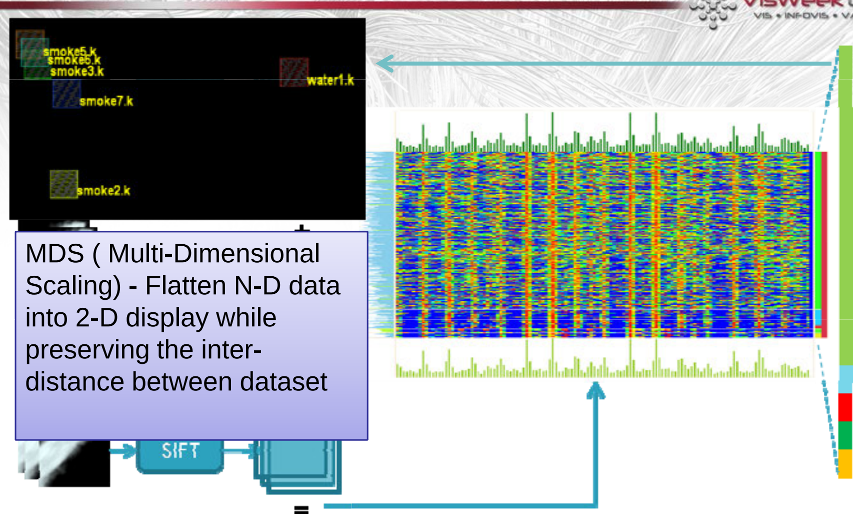
3D SIFT



Cluster Analysis on Visual Contents

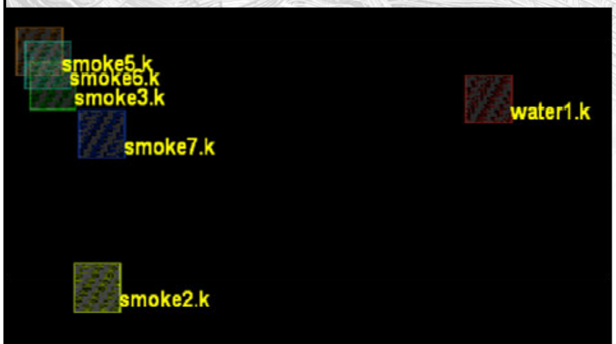


Feature Visualization in an Information Space



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

MDS Analysis: Categorization

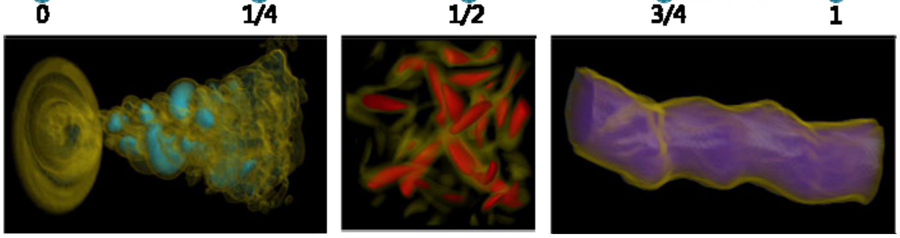


- water1: Water dropping from top-right to bottom-left corner
- smoke2: Smoke flow starting from the bottom-center
- smoke3: Smoke flow narrower than smoke2
- smoke5: Smoke flow similar with smoke3
- smoke6: Smoke flow similar with smoke3 and 5
- smoke7: Smoke flow similar with smoke3,5, and 6 but different direction

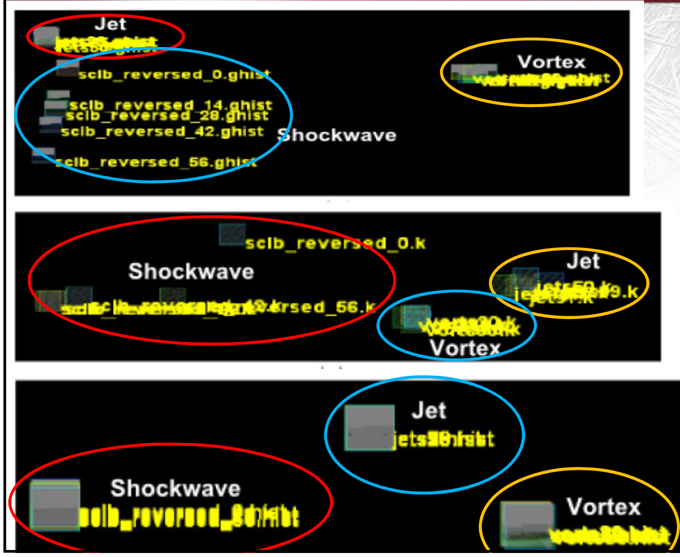
1. Categorize different groups of flows
2. Distinguish different features within same category

Categorization Of 3D Flows

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



MDS Analysis



Global histograms

3D SIFT

Local histograms

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

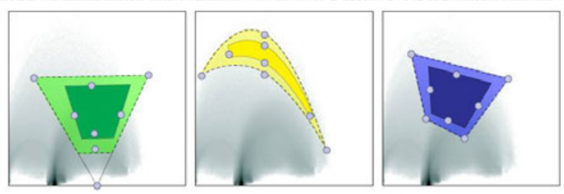
- Determines how features are expressed into visual manifestations = their visual appearance
- Features may control the rendering pipeline at various stages:
  - local color and opacity (mapping via transfer function)
  - scene composition (local sparseness, warping by lenses)
  - rendering style (lighting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

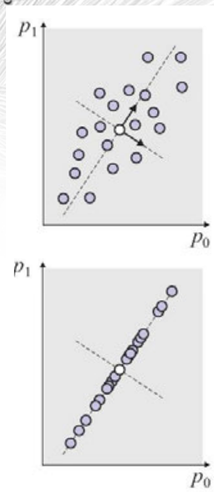
- but they do so in complex ways
  → lots of tedious tweaking is required

[Rezk-Salama 06]

Parameter Aggregation

We can learn these small deviations by observing a few datasets

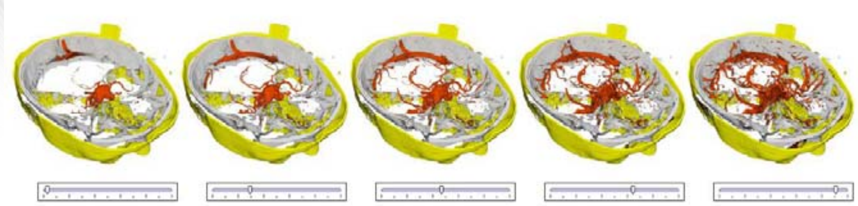
- encode the parameters into an N-D vector
- find the principal component of the vectors (the main Eigenvector)
- project all other vectors onto this Eigenvector
- the min and max then represent the min and max of the slider



[Rezk-Salama '06]

Transfer Function Simplification

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



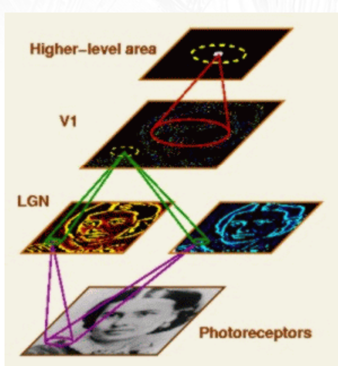
- works here since in CT usually only small deviations exist
- but these small deviations require complex interactions in the transfer function domain

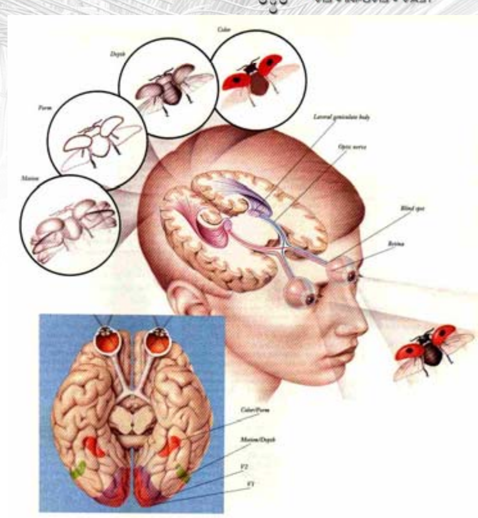
[Rezk-Salama '06]

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

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- 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

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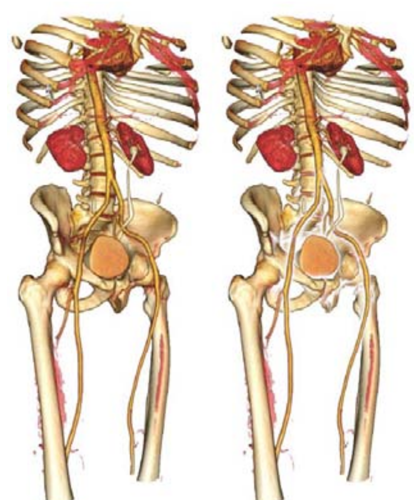
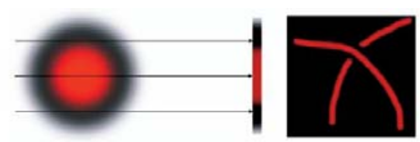
- Visual transform of data features to direct a viewer's attention
  - shape (edges, silhouettes)
  - surface (curvatures, suggestive contours)
  - size
  - intensity and color
  - texture
- Enhancement / suppression makes this more effective
  - opacity controls presence
  - rendering style and texture 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)

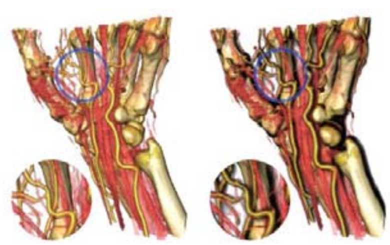
Halos



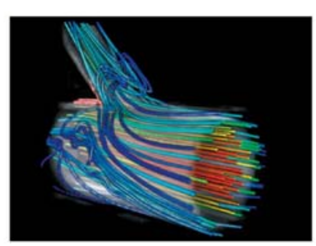
no halos with halos

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.

Two Levels Of Abstraction

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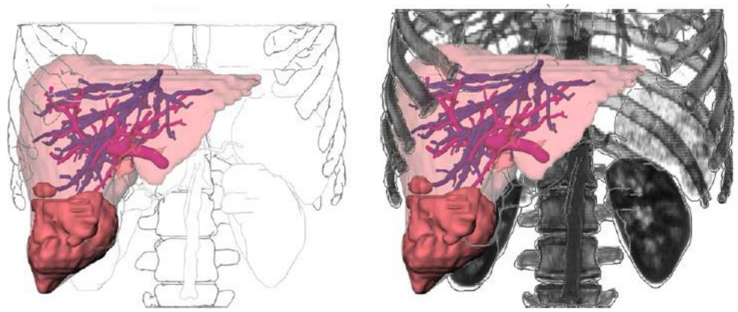
  - stylized depiction: silhouettes, contours, pen+ink, stippling, hatching, etc.

- 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

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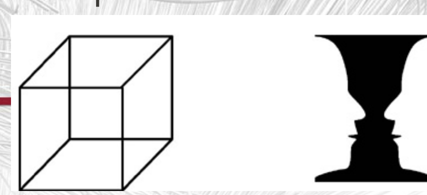
  - in contrast to computer vision, WE design/create the scene
  - this design guides the attention of the viewer
  - guidance determined by visualization goals
- Therefore it is important to understand mechanism of attention

Visual Recognition and Attention

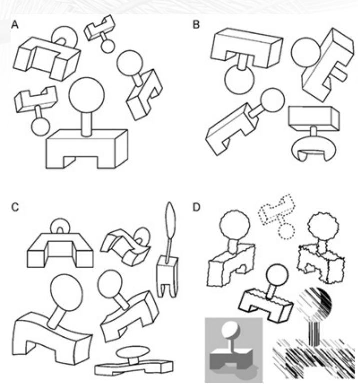
- Two opposing theories:
  - Gestalt
  - Feature integration
- Gestalt theory
  - top-down approach
  - proposes that the operational principle of the brain is holistic, parallel, and analog, with self-organizing tendencies
  - important in user interface design (button grouping, etc)
- Feature integration 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

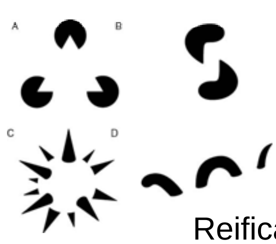
Emergence



Multi-Stability



Invariance



Reification

Gestalt Theory: Opposing Examples

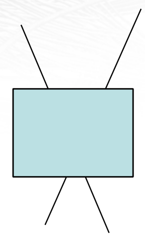
- **Selective-Encoding:**
  - involving one to distinguish what is important in a problem and what is irrelevant (i.e., filtering)
- **Selective-Comparison:**
  - identifying information by finding a connection between acquired knowledge and experience
- **Selective-Combination:**
  - identifying a problem 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



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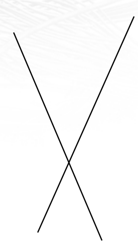


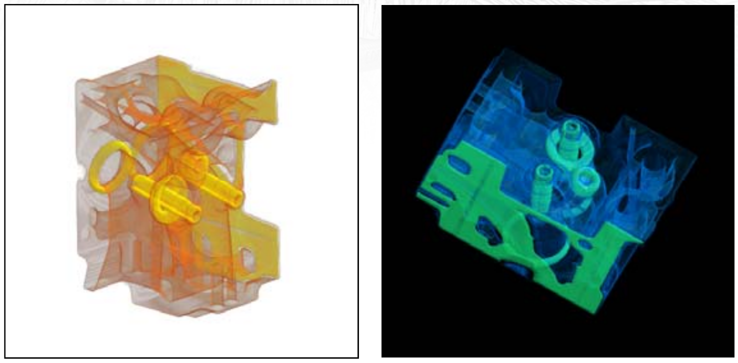
Ghosting

Topic 4: User Studies Are Important

- 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

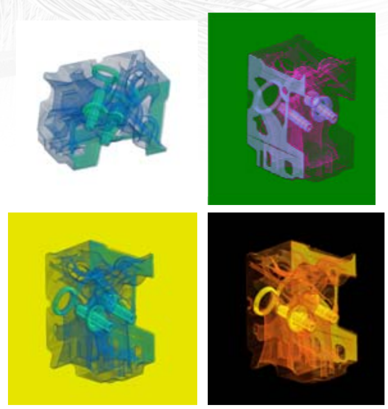
Sample Testing Scenario

- Which color transfer function shows more detail?



Putting Conjoint Analysis to the Test

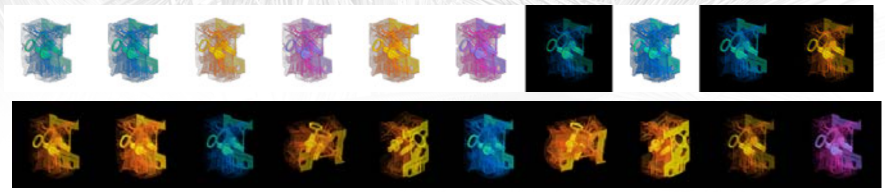
- Performed a user study on a multi-parametric visualization scenario
- On a set of 2700 images of engine blocks, we varied:
  - color transfer function (3)
  - rendering mode (5)
  - viewpoint (6)
  - image resolution (2)
  - ray step size (3)
  - background (5)
- Tested
  - 786 respondents
  - 20 pair-wise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



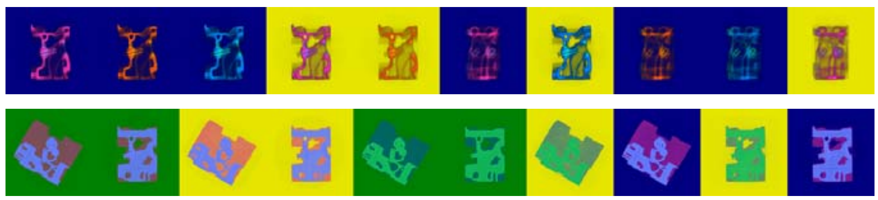
[Giesen '07]

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

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More and Up-To-Date Information

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

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