Parameter-Space Exploration in Visualization

Stefan Bruckner

Institute of Computer Graphics and Algorithms
Vienna University of Technology

Volumetric Data Spaces

- Multidimensional parameter space, 3D output space $f(x): \mathbb{R}^N \rightarrow \mathbb{R}^3$

Ensemble Data (1)

- Common approach for analyzing complex computational models
  - Climate and weather simulations, parameter studies for engineered systems, etc.
- Generated by computational simulations using different inputs, models, or parameters
- Multiple samples of a volumetric data space $\rightarrow$ volumetric ensemble data set

Ensemble Data (2)

- Several different aspects of ensemble visualization
  - Query: search and retrieval for ensemble members with certain characteristics
  - Aggregation: probability/uncertainty quantification and visualization
  - Classification: abstraction and categorization of the ensemble

$2^{1/2}$D Data Spaces

- Volume Visualization: Non-trivial mapping of data values to visible structures
- Auxiliary Visualizations: Simple depictions to assist in finding relevant value ranges
Isosurface Statistics

- Approaches using distributions over the range of data values
  - Isosurface areas [Carr et al. 2006]
  - Contour spectrum [Bajaj et al. 1997]
  - Gradient magnitude [Kniss et al. 2002]

No direct quantification of relationships between isosurfaces

Scalar Field Topology

- Methods based on topology analysis of the scalar field
  - Contour trees [Carr et al. 2000]
  - Hyper Reeb graphs [Fujisiro et al. 2000]
  - Skeleton trees [Takahashi et al. 2006]

Focus on topological relationships, sensitive to noise (need simplification)

Example

Similarity Maps – Key Aspects

- Treat isosurfaces as a whole instead of individual voxels
- Characterize the shape of every isosurface
- Quantify their similarity by comparing all isosurface shapes

Isosurface Representation

- Each isosurface is represented by its distance transform

Similarity Measure (1)

- Regard the distances to a pair of isosurfaces as random variables $X, Y$
  - Characterize the amount of information they share to evaluate similarity
- Mutual Information: Commonly used information-theoretic measure
  - Measures how much knowing one variable reduces the uncertainty about the other
Similarity Measure (2)

**Mutual Information**

Marginal entropies of \(X, Y\)

\[
I(X, Y) = H(X) + H(Y) - H(X, Y)
\]

Joint entropy of \(X\) and \(Y\)

- \(X\) and \(Y\) are independent: \(I(X, Y) = 0\)
- \(X\) and \(Y\) are identical: \(I(X, Y) = H(X) = H(Y)\)

Normalized measure

\[
\hat{I}(X, Y) = \frac{2I(X, Y)}{H(X) + H(Y)}
\]

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Joint Entropy

\[
H(X, Y) = -\sum_{x \in X} \sum_{y \in Y} p_{X,Y}(x, y) \log p_{X,Y}(x, y)
\]

Joint probability distribution of \(X\) and \(Y\)

- Requires knowledge of the joint probability distribution of \(X\) and \(Y\)
- Simple estimation method using the joint histogram of \(X\) and \(Y\)

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Joint Distribution Estimation

Joint distribution \(p_{X,Y}\)

Isosurface \(h_d\)

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Isosurface Similarity Map

Depicts the mutual information of each combination of isosurfaces.

Isosurface Similarity Distribution

Depicts the average similarity within a subset of isovalues.

Similarity-Enhanced Isosurfaces (1)

- Neighboring isosurface may exhibit subtle variations.
- Can have significant impact, e.g., for stenosis assessment [Lundström et al. 2007]
- Similarity-based degree-of-interest \(\gamma(x)\) in a sample \(x\) not on the isosurface \(h\)

\[
\gamma(x) = \prod_{y \in S(x)} SM(h, f(y))
\]

Sample position

Similarity map value at \(y\)

Chosen iso value

Neighborhood of \(x\)

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Similarity-Enhanced Isosurfaces (3)

Mapping between user interface and isovalue is typically linear
- Examples are slider widgets, mouse movement, etc.
- Data-dependent nonlinear visual response to user interaction
- Makes it more difficult to investigate transitional value ranges
- Control derivative of the mapping function using the similarity between neighboring isovales

Representative Isovalue Detection (1)

Find “good” isovales for a given data set without requiring parameter tuning
- Representative: Each isovale exhibits high similarity to many other isovales
- Distinct: The individual chosen isovales have low mutual similarity
- Reorder all isovales according to these criteria by recursively evaluating the similarity distribution

Detection Algorithm (1)

Step 1: Recursive pivoting based on the maximum of the similarity distribution
Step 2: Greedy selection and penalization of similar isosurfaces

Detection Algorithm (2)

Step 1: Pivoting
- Find maximum of similarity distribution
- Store maximum weighted by number of represented values
- Repeat recursively above and below the chosen value

Detection Algorithm (3)

Step 2: Selection
- Select isovale with highest priority as determined in the previous step
- Penalize remaining candidates based on similarity with the chosen value
- Continue until all isovales have been processed
Multimodal Surface Similarity (1)

Multimodal Surface Similarity (2)

Multimodal Surface Similarity (3)
Fluid simulation is heavily used in movies and television. Most common animation packages include solvers or offer add-ons. Problem: Difficult to control for visual effects artists.

- Fluid simulation is heavily used in movies and television.
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- Tens of parameters
- Hard to predict results
- Time-consuming trial & error

Autodesk Maya 2010
Sampling and Simulation (1)

Sampling: generation of a set of parameter vectors
Simulation: execution of fluid solver for each single parameter vector
Different sampling strategies
- Unconstrained random
- Latin hypercube
- Importance sampling
Advantage of unconstrained random sampling: can be terminated at any time

Segmentation (1)

To simplify further processing, simulation sequences are split into short segments
Segments have high coherency, are continuous in time
A segment representative is chosen and used to represent each segment
Similar to keyframe extraction used in video abstraction

Segmentation (3)

Dissimilarity measure: sum of squared intensity differences between time step i and time step i+1
Segmentation (5)
- Continues until number of segments is higher than specified maximum segment count
- Then terminates when the minimum similarity exceeds a threshold

Segmentation (6)
- Segment representatives: minimize difference between the cumulative dissimilarity of predecessors and successors

Clustering (1)
- Identify “phases” over multiple parameter settings
- Group similar segments of all simulation sequences
- Density-based clustering using the DBSCAN algorithm [Ester et al. 1996]
- Each segment representative is weighted by the number of time steps in the segment

Clustering (2)
- Simple intensity-based measure for the dissimilarity between two segments
  - Sum of squared intensity differences of the segment representatives
  - Additional weight based on the temporal distance for segments of the same sequence

Visualization (1)
Visualization (2)

Cluster Timeline
- Visualize time dependent cluster memberships in a compact layout
- **Global rank** $r_G$ of a cluster:
  number of time steps covered ×
  number of contained sequences
- **Temporal rank** $r_T$ of a cluster:
  number of member sequences within a time interval $(t_s, t_e)$

Layout Generation
- For each time interval, cluster items are placed on the canvas sorted by $r_G \cdot r_T$

Time interval × 1

Temporal Zoom
- Temporal levels-of-detail by increasing the time interval

Time interval × 2
Temporal Zoom

- Temporal levels-of-detail by increasing the time interval
  - time interval \times 3

Sequence Paths

- Connections between all cluster items a sequence passes through

Item Selection

- Selection searches for member sequences of clusters within corresponding time intervals

Item Details

- Context menu depicting the nearest neighbors of the temporal medoid

Parameter View (1)

- Visualizes the distribution of parameter vectors within each cluster
- Additional weighting of vectors based on similarity to the cluster medoid
Parameter View (2)