Perception-Driven Techniques for Large Volume Data Analysis and Visualization

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Outline

• Introduction and motivation
  – Large data sets
  – Multiresolution visualization
  – Traditional solution vs. perception-driven solution
• Background
  – Wavelet transform
  – Hierarchical data representation
• Image-based quality metric
• Volume data quality assessment
Large Data Sets

• Scientific, medical, engineering, …
• Spatial, temporal, variable, …
• Gigabyte, terabyte, petabyte, exabyte, …

Multiresolution Visualization

• Large data sets make interactive visualization difficult
  – High (main + video) memory requirement
  – Slow I/O, slow rendering

• Multiresolution volume visualization
  – Adaptive data exploration
  – “Overview first, zoom and filter, and then details-on-demand” [SHNEIDERMAN 92]
Cognitive Capacity vs. Data Growth

• “Human cognitive capacity remains flat while our ability to collect and generate data continues to grow at an exponential rate.”

Perception-Driven Techniques

• Quantitative metrics for parameter choices
  – LOD selection and rendering
  – Image-based data quality estimation
  – Present visually important information

• Extract statistical information from the data
  – Volume data quality evaluation
  – Feature representation in multiscale manner
  – Incorporate perceptual reasoning

Reference: Visualization and Knowledge Discovery: Recommendations from the DOE/ASCR Workshop on Visual Analysis and Data Exploration at Extreme Scale, 2007. (Image courtesy Jeffrey Heer)
Image-Based Quality Metric

overview: MSE, 8.6%  SNR, 8.5%  image, 8.3%

full resolution, 929

Multiscale Quality Assessment

(a) mean shift  (b) voxel misplacement  (c) averaging filter  (d) salt-and-pepper noise

Ours: best worst
MSE/PSNR: best worst
Wavelet Transform and Hierarchical Data Representation

Wavelet Transform on 2D Image
Wavelet Transform on 2D Image

1\textsuperscript{st} level
L: low-pass filtered
H: high-pass filtered

LL1
LH1
HL1
HH1

Wavelet Transform on 2D Image

2\textsuperscript{nd} level
L: low-pass filtered
H: high-pass filtered

LL1
→
LL2
LH2
HH2
HL2
HH2
Wavelet Transform on 2D Image

3rd level
L: low-pass filtered
H: high-pass filtered

LL2
→
LL3
LH3
HL3
HH3

Wavelet Transform on 3D Volume

L: low-pass filtered
H: high-pass filtered

LLL
LLH
LHL
HLL
LHH
HLH
HHL
HHH

[MURAKI 92]
Wavelet Transform

- Spatial domain → spatial-frequency domain
- Separable wavelet transform
- Wavelet compression
  - Low-pass filtered data: summary information
  - Wavelet coefficients: detail information
  - Coefficients are “sparse”, thus can be utilized in compression
  - Lossy and lossless compression
- Wavelet reconstruction

Hierarchical Data Representation

- Image and video
  - Laplacian pyramid [BURT et al. 83]
  - Multiresolution video [FINDELSTEIN et al. 96]
- 3D volume data
  - Laplacian pyramid [GHAVAMNIA et al. 95]
  - Octree hierarchy [LAMAR et al. 99]
  - Wavelet tree [GUTHE et al. 02]
- Time-varying volume data
  - Time-space partitioning (TSP) tree [SHEN et al. 99]
  - 4D hierarchy [LINSEN et al. 02]
  - Wavelet-based TSP tree [WANG et al. 04]
Wavelet Tree

- Octree-based space partition
- Block-wise wavelet transform and compression
- Error metric calculation

Image-Based Quality Metric for LOD Selection
Outline

- Importance values of data blocks
  - Emission (of a data block)
  - Occlusion (among data blocks)
  - Distortion (of low and high resolution data blocks)
  - Perceptually-uniform CIELUV color space
- Real-time update of quality metric
  - Summary table scheme
  - GPU-based visibility estimation

Volume Rendering Integral

- Volume rendering integral [MAX 95]
  \[ I_r = \int_0^D \tilde{c}(s(\tilde{x}(\lambda))) \exp\left(-\int_0^\lambda \tau(s(\tilde{x}(\lambda'))d\lambda')d\lambda \right) \]
  (a) emission \hspace{1cm} (b) attenuation

- Discretized volume rendering integral
  \[ I_r = \sum_{i=0}^n c(s_i)\alpha(s_i)\prod_{j=0}^{i-1}(1 - \alpha(s_j)) \]
  (a) emission \hspace{1cm} (b) attenuation
Importance Value Design

\[ I_b = \frac{(c(\mu)\alpha(\mu) \cdot t \cdot a) \cdot \nu \cdot \varepsilon}{(a) \text{ emission} \hspace{1cm} (b) \text{ attenuation} \hspace{1cm} (c) \text{ distortion}} \]

- \( \mu \): mean scale data value
- \( c(\mu)\alpha(\mu) \): color and opacity transfer function
- \( t \): average thickness
- \( a \): screen projection area
- \( \nu \): estimated visibility
- \( \varepsilon \): distortion of block \( b \) and its child blocks

Multiresolution Error Evaluation

\[ \varepsilon_{ij} = \tilde{\sigma}_{ij} \cdot \mu_i^2 + \tilde{\mu}_j^2 + C_1 \cdot \tilde{\sigma}_{ij}^2 + \tilde{\mu}_j^2 + C_2 \]

\[ \frac{1}{2\tilde{\mu}_i \tilde{\mu}_j + C_1} \cdot \frac{1}{2\tilde{\sigma}_{ij} \tilde{\mu}_j + C_2} \]

\[ \tilde{\sigma}_{ij} \]: covariance between \( b_i \) and \( b_j \)
- \( \tilde{\mu} \): mean value; \( \tilde{\sigma} \): standard deviation
- \( C_1 \) and \( C_2 \): small constants; \( N \): # of voxels in the block

- \( \tilde{\sigma}_{ij} = \frac{1}{N-1} \sum_{k=1}^{N} (x_{ik} - \tilde{\mu}_i)(x_{jk} - \tilde{\mu}_j) \)
- \( \tilde{\mu}_i = \frac{1}{N-1} \sum_{k=1}^{N} (x_{ik} - \tilde{\mu}_i)^2 \)
- \( \tilde{\sigma}_j = \frac{1}{N-1} \sum_{k=1}^{N} (x_{jk} - \tilde{\mu}_j)^2 \)

[WANG et al. 04]
Multiresolution Error Evaluation

\( \tilde{x} \) and \( \tilde{\mu} \) : CIELUV color values

\[
\tilde{x} - \tilde{\mu} = \Delta E(f(\text{rgb}(x)\alpha(x)), f(\text{rgb}(\mu)\alpha(\mu)))
\]

\( \Delta E \) : CIELUV color difference

\[
\Delta E = \sqrt{\Delta L^2 + \Delta u^2 + \Delta v^2}
\]

\( \varepsilon_i \) : multiresolution error

\[
\varepsilon_i = \sum_{j=0}^{7} \varepsilon_{ij} + \max \{ \varepsilon_j | j=0 \}
\]

Summary Table Scheme

- Update metric when transfer function changes
  - Size of data range << # of voxels in the volume [LAMAR et al. 03]
  - Count frequencies of unique error terms: \( x_i, x_j \), and \( (x_i, x_j) \)
  - Store histogram and correspondence tables
  - Runtime table lookup

<table>
<thead>
<tr>
<th>data set</th>
<th>space (overhead)</th>
<th>update time</th>
</tr>
</thead>
<tbody>
<tr>
<td>VisWoman</td>
<td>9.22MB (1.07%)</td>
<td>5s</td>
</tr>
<tr>
<td>RMI</td>
<td>44.1MB (0.57%)</td>
<td>13s</td>
</tr>
</tbody>
</table>
Visibility Estimation

• Evaluate approximate visibility of data blocks
  - Render low resolution data
  - Draw front-to-back view-aligned slices
  - \( \nu = 1 - \alpha \), where \( \alpha \) is the average opacity on the occlusion map

CPU vs. GPU Solutions

• CPU solution
  - Read framebuffer when drawing slices
  - Iterate through alpha channel
  - Framebuffer reads become bottleneck

• GPU solution
  - Utilize summed area tables (SATs)
  - GL_EXT_framebuffer_object (FBO)
  - 3~4 times faster than CPU solution
LOD Selection

- User specifies the block budget
- Update importance values
  - $\nu$ per view
    - Only update a certain percentage of blocks
    - Postpone update if the view changes slightly
  - $\varepsilon$ per transfer function
- Priority queue for LOD refinement
- A list of blocks identified from greedy selection

Results – Timing

<table>
<thead>
<tr>
<th>data set (type)</th>
<th>VisWoman (short)</th>
<th>RMI (byte)</th>
</tr>
</thead>
<tbody>
<tr>
<td>volume dimension</td>
<td>512 * 512 * 1728</td>
<td>2048 * 2048 * 1920</td>
</tr>
<tr>
<td>volume size</td>
<td>864MB</td>
<td>7.5GB</td>
</tr>
<tr>
<td>block dimension</td>
<td>32 * 32 * 64</td>
<td>128 * 128 * 64</td>
</tr>
<tr>
<td>block size</td>
<td>128KB</td>
<td>1MB</td>
</tr>
<tr>
<td># non-empty blocks</td>
<td>9446</td>
<td>10499</td>
</tr>
<tr>
<td>compression ratio (lossless)</td>
<td>2.37:1</td>
<td>5.60:1</td>
</tr>
<tr>
<td>visibility (GPU, $512^2$ image)</td>
<td>0.151s</td>
<td>0.185s</td>
</tr>
<tr>
<td>prioritization (all blocks)</td>
<td>0.343s</td>
<td>0.563s</td>
</tr>
<tr>
<td>transfer function (256 levels)</td>
<td>5s</td>
<td>13s</td>
</tr>
</tbody>
</table>

3.0GHz CPU, 3GB memory, nVidia GeForce 7800 GT graphics card
Results – VisWoman Data Set

overview MSE, 80, 8.61% SNR, 79, 8.50% image, 77, 8.29%

full resolution, 929 color map

Results – VisWoman Data Set

MSE, 36 blocks SNR, 37 blocks image, 34 blocks
Results – RMI Data Set

MSE, 55 blocks
SNR, 55 blocks
image, 55 blocks

overview
visibility

Results – RMI Data Set

full resolution, 1237
pixel difference percentage
Multiscale Volume Data Quality Assessment

Motivation

- We may use any type of non-original data
  - Quantized (e.g., floating → byte/short)
  - Compressed (e.g., lossy compression)
  - Filtered (e.g., Gaussian smooth/blur)
  - Reduced (e.g., down sampling)
  - Distorted (e.g., noise)
  - Corrupted (e.g., lost in transmission)
- How to measure data quality loss introduced in different versions of data?
Solution

• Extract features from the original data in the wavelet domain
  – Multiscale wavelet decomposition
  – Wavelet subband analysis – global information
  – Collect important coefficients – local information
  – Define distance metrics
• Use features for quality assessment
  – Features as “carry-on” information
  – Reduced-reference approach

Generalized Gaussian Density

\[
p(x) = \frac{\beta}{2\alpha\Gamma(\frac{1}{\beta})} \exp\left(-\frac{|x|^\beta}{\alpha}\right)
\]

\(\Gamma\) Gamma function
\(\alpha\) scale parameter
\(\beta\) shape parameter

= 2, Gaussian distribution
= 1, Laplacian distribution

Lena image, HL1 subband
\(\beta = 0.5\)
\(\alpha = 1.5\)
Generalized Gaussian Density

Kullback-Leibler Distance

• Quantify the difference of wavelet coefficient distribution between the distorted and the original data

\[ d(p \parallel q) = \sum_{i=1}^{M} P(i) \log \frac{P(i)}{Q(i)} \]

*P*: wavelet subband coefficient histogram approximated with GGD parameter( \( \alpha \), \( \beta \) )

*Q*: wavelet subband coefficient histogram of the distorted data

\[ D = \log(1 + \sum_{i=1}^{g} d(p_i \parallel q_i)) \]

*D*: the KLD between the distorted and original data
Wavelet Coefficient Selection

- Coefficients of large magnitude
  - Correspond to abrupt features like edges or boundaries
  - Along the tails of the marginal coefficient distribution
- Neighboring near-zero coefficients
  - Correspond to homogeneous regions
  - Close to the zero peak of the marginal coefficient distribution
- Modulated by visual importance
  - Consider opacity and visibility
  - Approximate used low-resolution data

Coefficient Scan Order

raster scan

Morton scan
Feature Representation

Quality Assessment – Quantization
Quality Assessment – Gaussian Filter

Ours:  
MSE/PSNR:  

Quality Assessment – Cross Comparison

Ours:  
MSE/PSNR:  

<table>
<thead>
<tr>
<th>type</th>
<th>type</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D rank</th>
<th>MSE</th>
<th>PSNR</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean shift</td>
<td>mean shift</td>
<td>8.8428e-5</td>
<td>6.9776e-7</td>
<td>2.3914e-2</td>
<td>0.0239</td>
<td>4</td>
<td>1.8691e+3</td>
<td>48.1648</td>
</tr>
<tr>
<td>misplacement</td>
<td>voxel displacement</td>
<td>1.5386e-2</td>
<td>1.1612e-1</td>
<td>4.6497e-3</td>
<td>0.1223</td>
<td>3</td>
<td>1.5397e+3</td>
<td>49.0066</td>
</tr>
<tr>
<td>averaging</td>
<td>voxel displacement</td>
<td>1.6449e+0</td>
<td>5.4319e-1</td>
<td>1.4596e-3</td>
<td>0.7073</td>
<td>2</td>
<td>1.9289e+5</td>
<td>28.0279</td>
</tr>
<tr>
<td>noise</td>
<td>voxel displacement</td>
<td>1.7343e+0</td>
<td>7.8530e-1</td>
<td>9.7468e-3</td>
<td>0.9685</td>
<td>1</td>
<td>1.2152e+4</td>
<td>40.0347</td>
</tr>
</tbody>
</table>
Summary

• Applied perception in visualization
  – Image-based quality metric
    • Backward approach (from image to data)
    • Evaluate data contribution in rendering
    • Precompute summary tables
    • Runtime update visibility for LOD decision
  – Volume data quality assessment
    • Multiscale approach (in the wavelet domain)
    • Use GGD to capture wavelet coefficient distribution
    • Select visually important coefficients
    • Quantify data quality loss in different versions

References

References


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