Perception-Driven Techniques for Large Volume Data Analysis and Visualization

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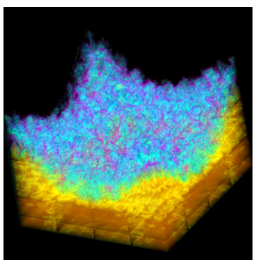
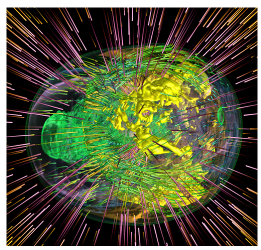
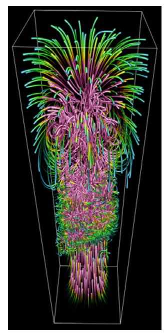
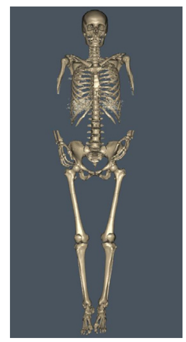
Outline

- 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, …

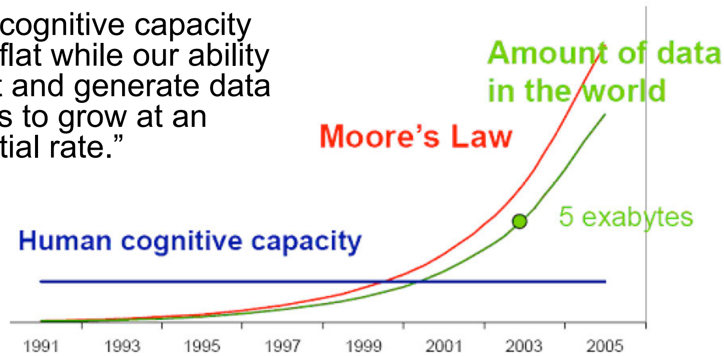





Multiresolution Visualization

- 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."

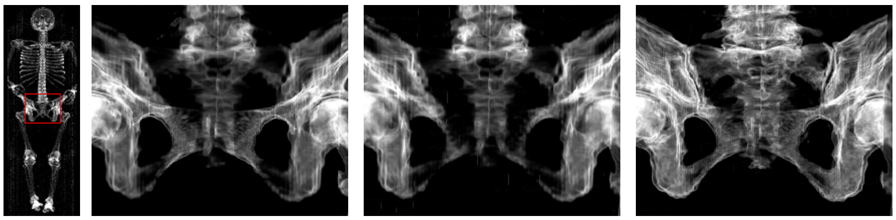


- Reference: Visualization and Knowledge Discovery: Recommendations from the DOE/ASCR Workshop on Visual Analysis and Data Exploration at Extreme Scale, 2007. (Image courtesy Jeffrey Heer)

Perception-Driven Techniques

- Quantitative metrics for parameter choices
  - LOD selection and rendering
  - Image-based data quality estimation
  - Present visually importance information
- Extract statistical information from the data
  - Volume data quality evaluation
  - Feature representation in multiscale manner
  - Incorporate perceptual reasoning

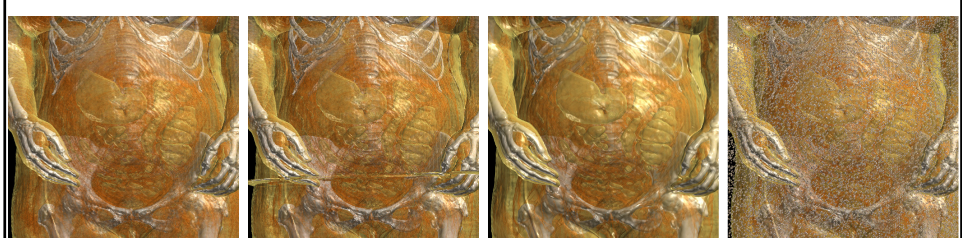
Image-Based Quality Metric



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

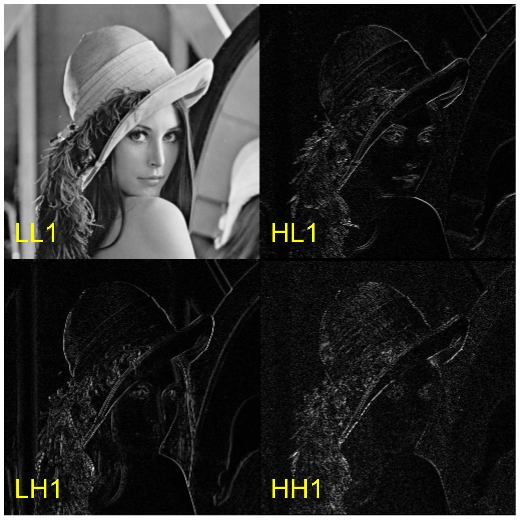
Ours: best worst

MSE/PSNR: best worst

Wavelet Transform and
Hierarchical Data Representation

Wavelet Transform on 2D Image

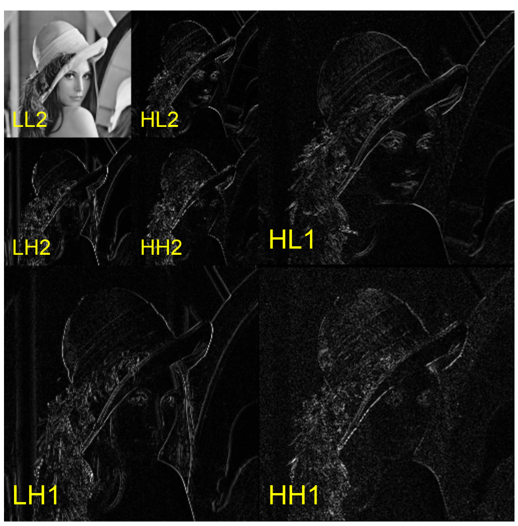
Wavelet Transform on 2D Image



1st level
L: low-pass filtered
H: high-pass filtered

LL1
LH1
HL1
HH1

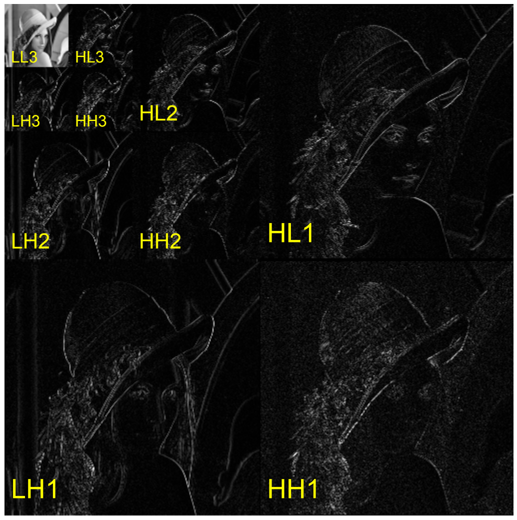
Wavelet Transform on 2D Image



2nd level
L: low-pass filtered
H: high-pass filtered

LL1
→
LL2
LH2
HL2
HH2

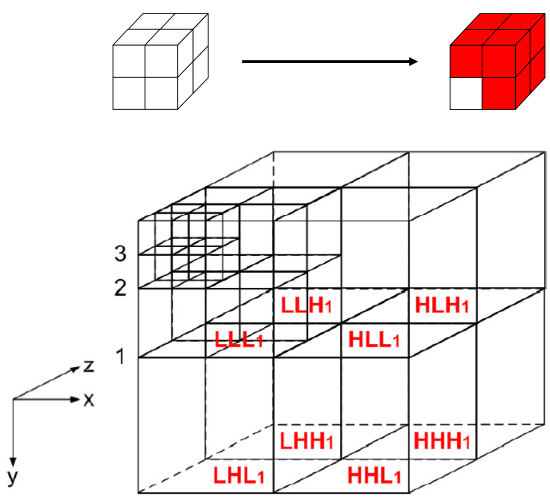
Wavelet Transform on 2D Image



3^{rd} level
L: low-pass filtered
H: high-pass filtered

LL2
→
LL3
LH3
HL3
HH3

Wavelet Transform on 3D Volume



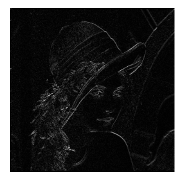
L: low-pass filtered
H: high-pass filtered

LLL
LLH
LHL
HLL
LHH
HLH
HHL
HHH

[MURAKI 92]

Wavelet Transform

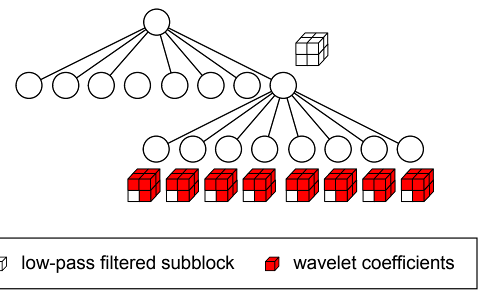
- Spatial domain → spatial-frequency domain
- Separable wavelet transform
- Wavelet compression
  - Low-pass filtered data: *summary* information
  - Wavelet coefficients: *detail* information
  - Coefficients are "sparse", thus can be utilized in compression
  - Lossy and lossless compression
- Wavelet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



Hierarchical Data Representation

- Image and video
  - Laplacian pyramid [BURT et al. 83]
  - Multiresolution video [FINKELSTEIN 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

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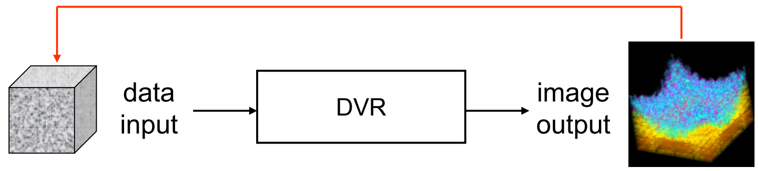
Outline



- 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]

$$I_r = \int_0^D \underbrace{\tilde{c}(s(\vec{x}(\lambda)))}_{(a)} \underbrace{\exp(-\int_0^\lambda \tau(s(\vec{x}(\lambda')))d\lambda')}_{(b)} d\lambda$$

- Discretized volume rendering integral

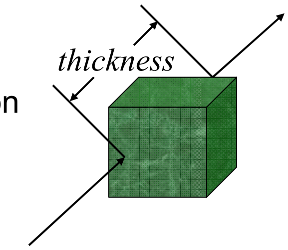
$$I_r = \sum_{i=0}^{n} \underbrace{c(s_i)\alpha(s_i)}_{(a)} \underbrace{\prod_{j=0}^{i-1}(1-\alpha(s_j))}_{(b)}$$

(a) emission
(b) attenuation

Importance Value Design

$$I_b = \underbrace{(c(\mu)\alpha(\mu)\cdot t \cdot a)}_{(a)} \cdot \underbrace{v}_{(b)} \cdot \underbrace{\varepsilon}_{(c)}$$

(a) emission
(b) attenuation
(c) distortion



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

Multiresolution Error Evaluation

$$\varepsilon_{ij} = \underbrace{\tilde{\sigma}_{ij}}_{(a)} \cdot \underbrace{\frac{\tilde{\mu}_i^2 + \tilde{\mu}_j^2 + C_1}{2\tilde{\mu}_i\tilde{\mu}_j + C_1}}_{(b)} \cdot \underbrace{\frac{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2 + C_2}{2\tilde{\sigma}_i\tilde{\sigma}_j + C_2}}_{(c)}$$

(a) covariance
(b) luminance distortion
(c) contrast distortion
structural similarity index
[WANG et al. 04]

$\tilde{\sigma}_{ij}$: 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

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

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

Multiresolution Error Evaluation

$\tilde{x}$ and $\tilde{\mu}$: CIELUV color values

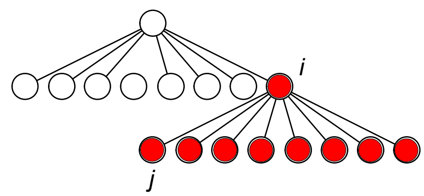
$$\tilde{x} - \tilde{\mu} = \Delta E(f(c_{rgb}(x)\alpha(x)), f(c_{rgb}(\mu)\alpha(\mu)))$$

ΔE : CIELUV color difference

$$\Delta E = \sqrt{\Delta L^{*2} + \Delta u^{*2} + \Delta v^{*2}}$$

ε_i : multiresolution error

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

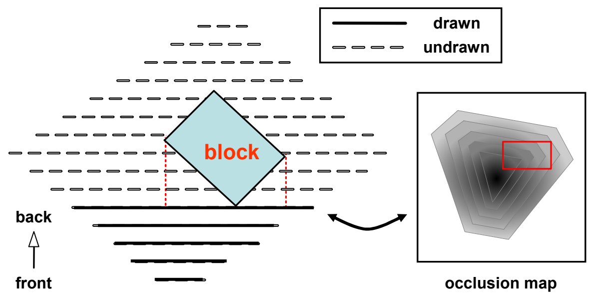


Summary Table Scheme

- 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

data set	space (overhead)	update time
VisWoman	9.22MB (1.07%)	5s
RMI	44.1MB (0.57%)	13s

Visibility Estimation



- Evaluate approximate visibility of data blocks
  - Render low resolution data
  - Draw front-to-back view-aligned slices
  - $v = 1 - \alpha$, where α 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

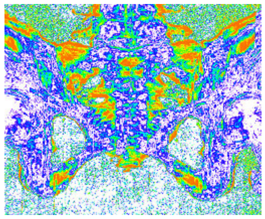
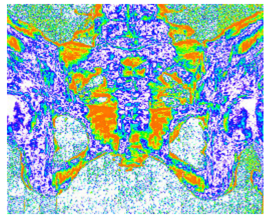
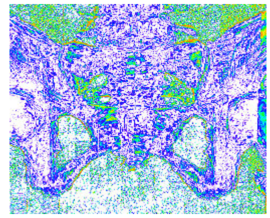
LOD Selection

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

Results – Timing

data set (type)	VisWoman (short)	RMI (byte)
volume dimension	512 * 512 * 1728	2048 * 2048 * 1920
volume size	864MB	7.5GB
block dimension	32 * 32 * 64	128 * 128 * 64
block size	128KB	1MB
# non-empty blocks	9446	10499
compression ratio (lossless)	2.37:1	5.60:1
visibility (GPU, 512^2 image)	0.151s	0.185s
prioritization (all blocks)	0.343s	0.563s
transfer function (256 levels)	5s	13s
3.0GHz CPU, 3GB memory, nVidia GeForce 7800 GT graphics card		

Results – VisWoman Data Set

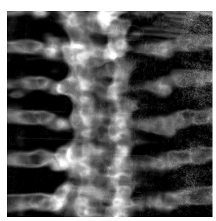
overview MSE, 80, 8.61% SNR, 79, 8.50% image, 77, 8.29%

full resolution, 929

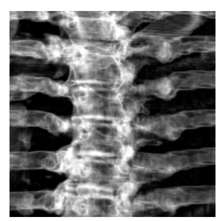
color map

Results – VisWoman Data Set

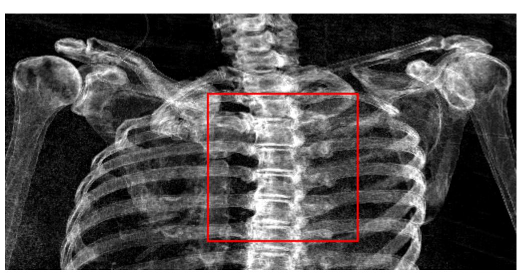
MSE, 36 blocks



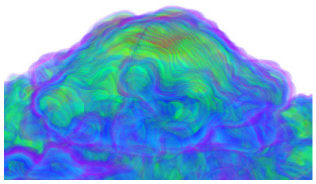
SNR, 37 blocks



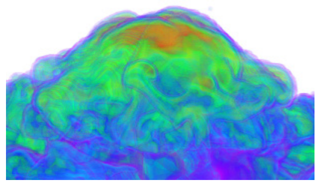
image, 34 blocks



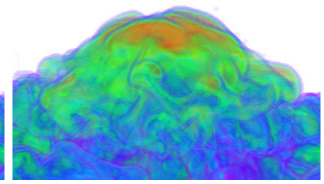
Results – RMI Data Set



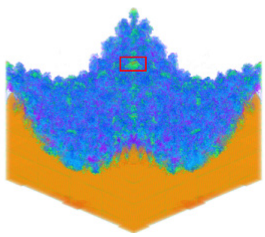
MSE, 55 blocks



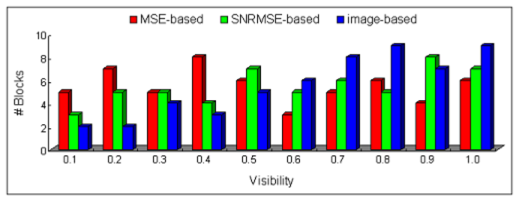
SNR, 55 blocks



image, 55 blocks

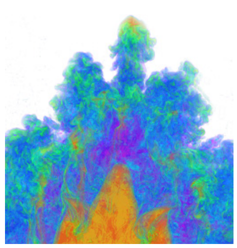


overview

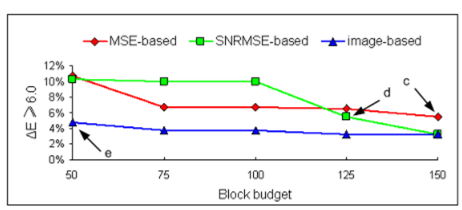


visibility

Results – RMI Data Set



full resolution, 1237



pixel difference percentage

Multiscale Volume Data Quality Assessment

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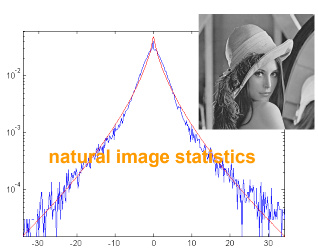
Motivation

- 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?

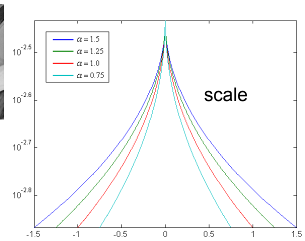
Solution

- 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

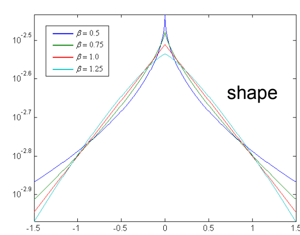
Generalized Gaussian Density



Lena image, HL_1 subband



β = 0.5



α = 1.5

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

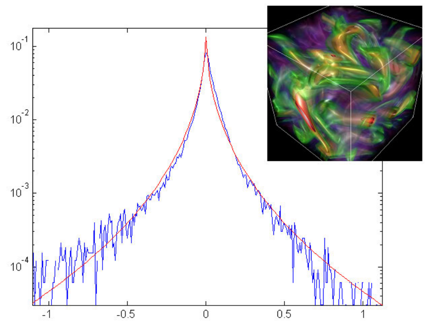
[MALLAT 99]

Γ Gamma function

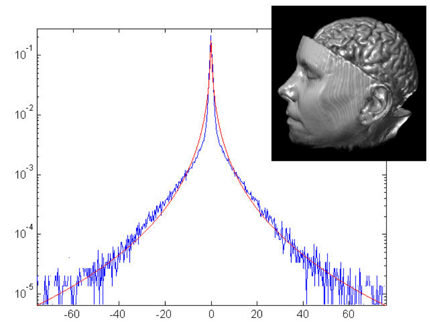
α scale parameter

β shape parameter
= 2, Gaussian distribution
= 1, Laplacian distribution

Generalized Gaussian Density



vortex data set, HHL_2 subband



brain data set, HLL_1 subband

Kullback-Leibler Distance

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

$$d(p \| q) = \sum_{i=1}^{M} P(i) \log \frac{P(i)}{Q(i)}$$

P: wavelet subband coefficient histogram approximated with GGD parameter(α , β)

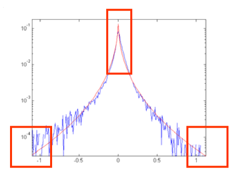
Q: wavelet subband coefficient histogram of the distorted data

$$D = \log(1 + \sum_{i=1}^{B} d(p^i \| q^i))$$

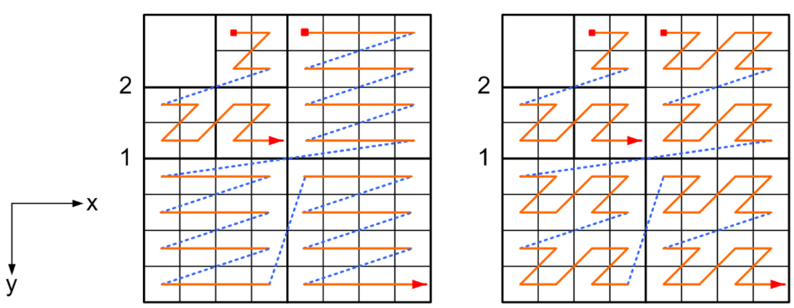
D: the KLD between the distorted and original data

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



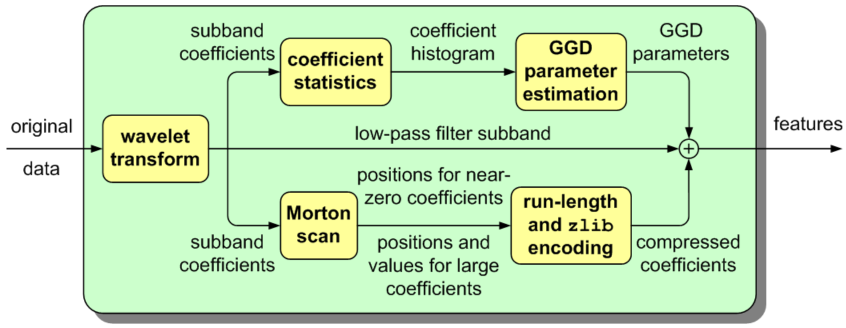
Coefficient Scan Order



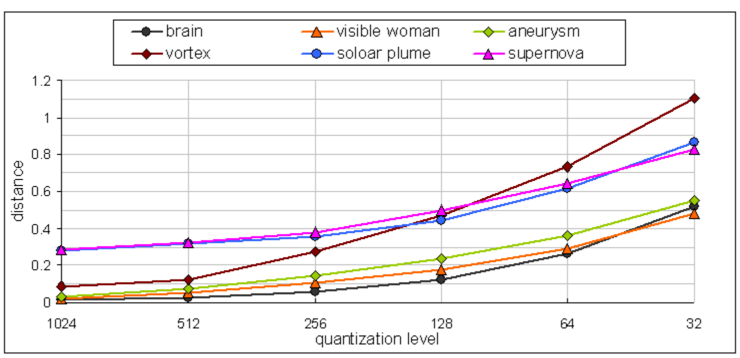
raster scan

Morton scan

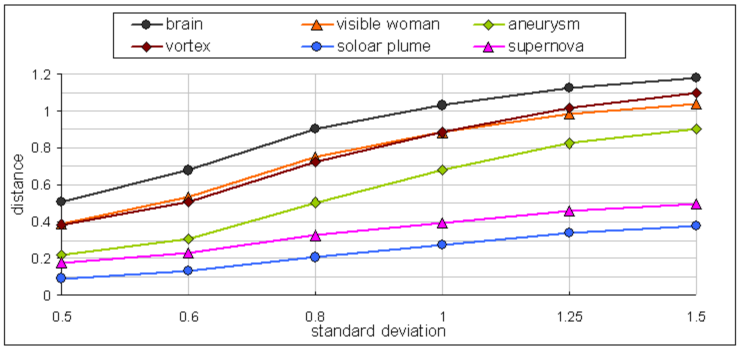
Feature Representation



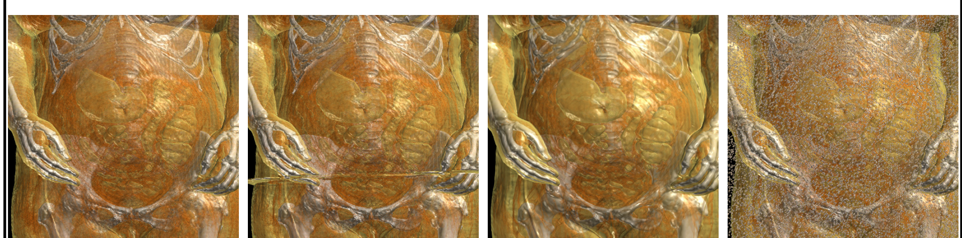
Quality Assessment – Quantization



Quality Assessment – Gaussian Filter



Quality Assessment – Cross Comparison



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

Ours: best worst

MSE/PSNR: best worst

type	D1	D2	D3	D	rank	MSE	PSNR	rank
mean shift	8.8428e-5	6.9770e-7	2.3914e-2	0.0239	4	1.8691e+3	48.1648	3
misplacement	1.5366e-2	1.1612e-1	4.6497e-3	0.1223	3	1.5397e+3	49.0066	4
averaging	1.6449e+0	5.4139e-1	1.4596e-3	0.7073	2	1.9289e+5	28.0279	1
noise	1.7343+0	7.8530e-1	9.7468e-3	0.9685	1	1.2152e+4	40.0347	2

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

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