SIGGRAPH ASIA 2018 TOKYO
CONFERENCE 4 – 7 December 2018
EXHIBITION 5 – 7 December 2018
Tokyo International Forum, Japan
SA2018.SIGGRAPH.ORG

GPU-Based Large-Scale Scientific Visualization

Johanna Beyer, Harvard University

Markus Hadwiger, KAUST

Course Website:

http://johanna-b.github.io/LargeSciVis2018/index.html

Part 4 -
Display-Aware Visualization and Processing

MOTIVATION


goal:
perform computations
at output resolution
250 megapixels
<1 megapixel visible


resolution level 0


resolution level 3

DISPLAY-AWARE IMAGE OPERATIONS

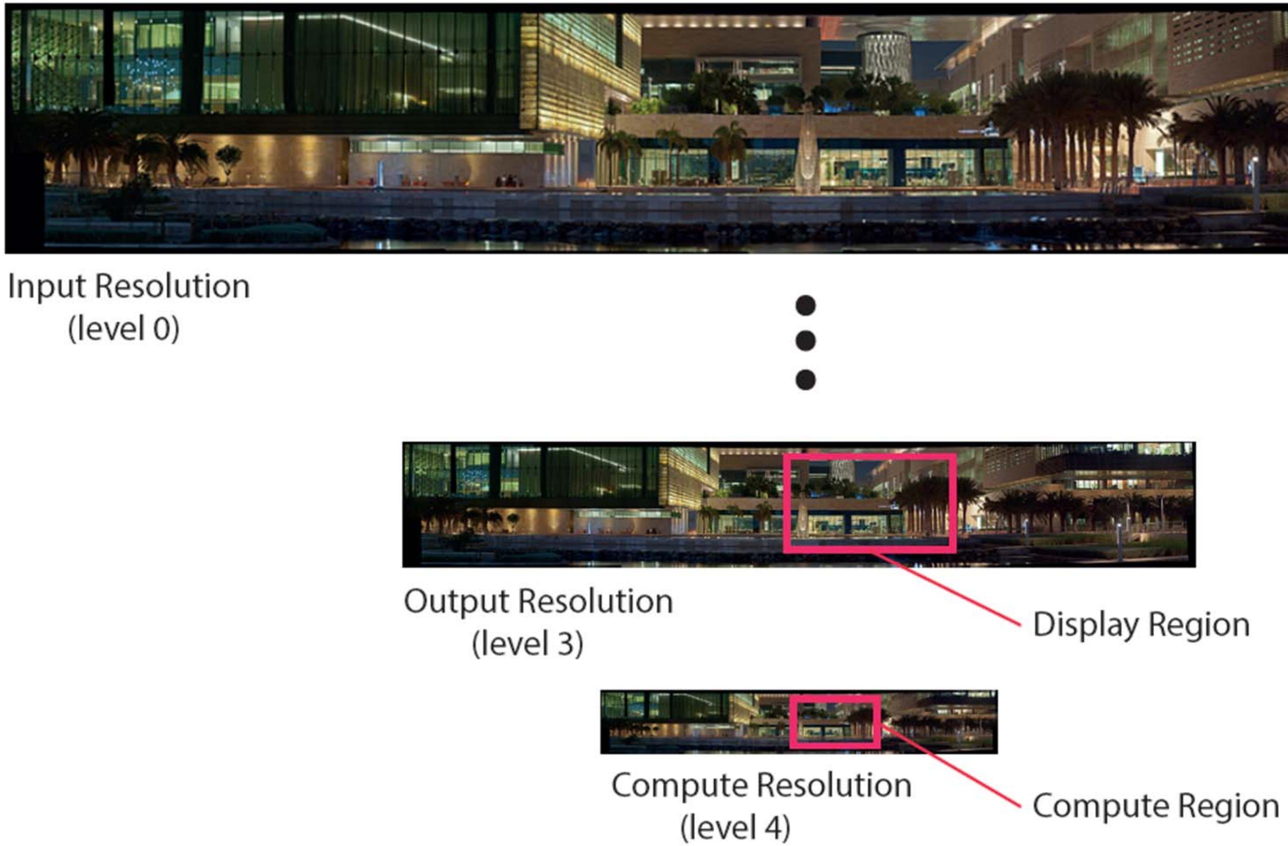


IMAGE PYRAMIDS

Dyadic image pyramids

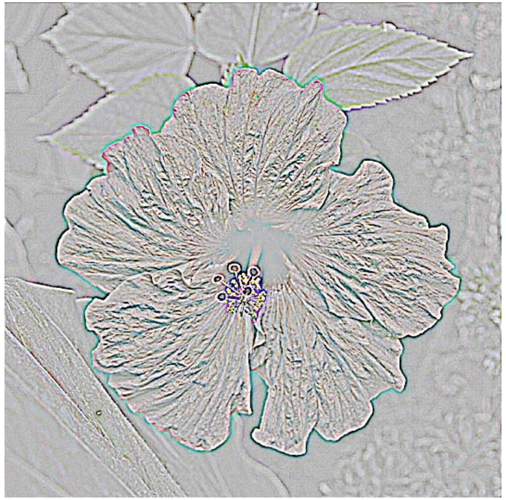
- Mipmaps [Williams 1983]: texture mapping (standard on GPUs)
- Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression

level 0 level 1 level 2 level 3

IMAGE PYRAMIDS

Dyadic image pyramids

- Mipmaps [Williams 1983]: texture mapping (standard on GPUs)
- Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression



level 0

level 1

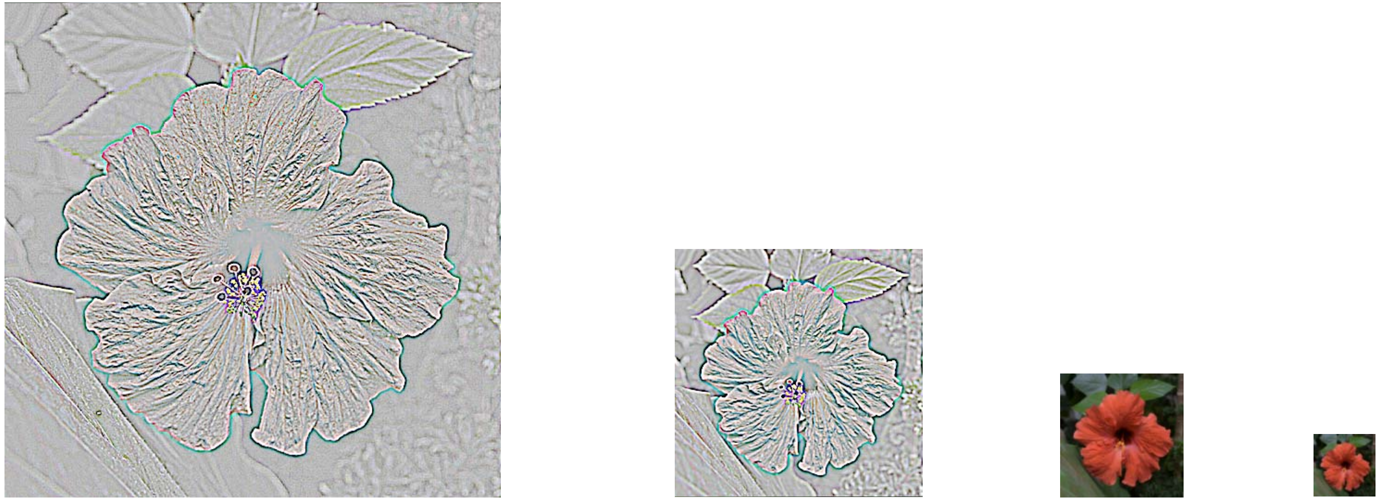
level 2

level 3

IMAGE PYRAMIDS

Dyadic image pyramids

- Mipmaps [Williams 1983]: texture mapping (standard on GPUs)
- Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression



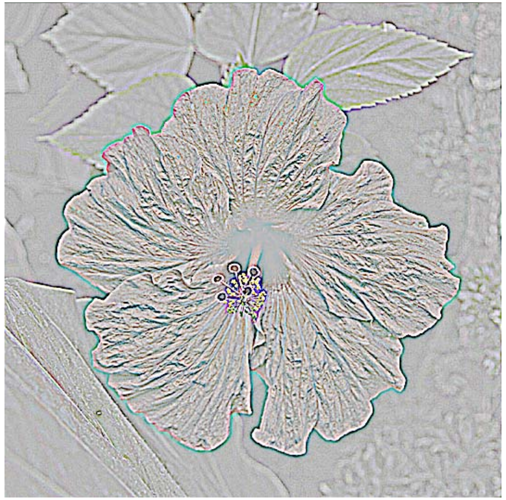
level 0 level 1 level 2 level 3

IMAGE PYRAMIDS

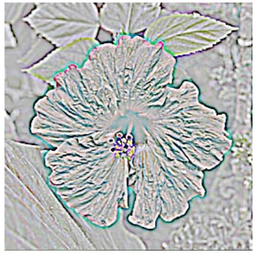
Dyadic image pyramids

- Mipmaps [Williams 1983]: texture mapping (standard on GPUs)
- Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression
- Sparse pdf maps [Hadwiger et al. 2012]

Laplacian pyramid



level 0



level 1

level 2

level 3

IMAGE PYRAMIDS

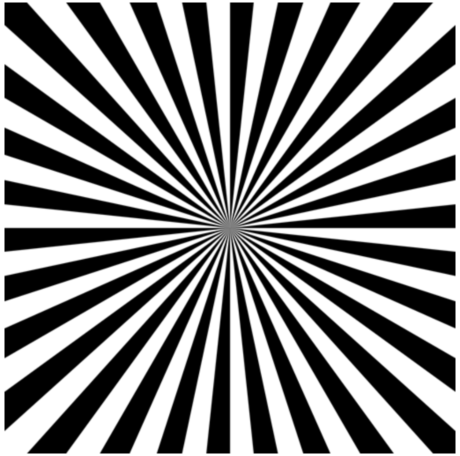
Dyadic image pyramids

- Mipmaps [Williams 1983]: texture mapping (standard on GPUs)
- Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression
- Sparse pdf maps [Hadwiger et al. 2012]

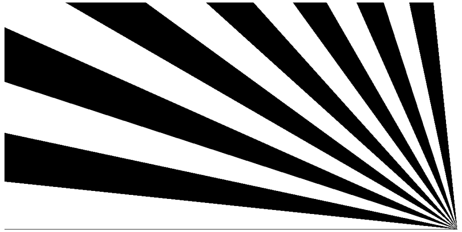
Local Laplacian filtering [Paris et al. 2011]

level 0 level 1 level 2 level 3

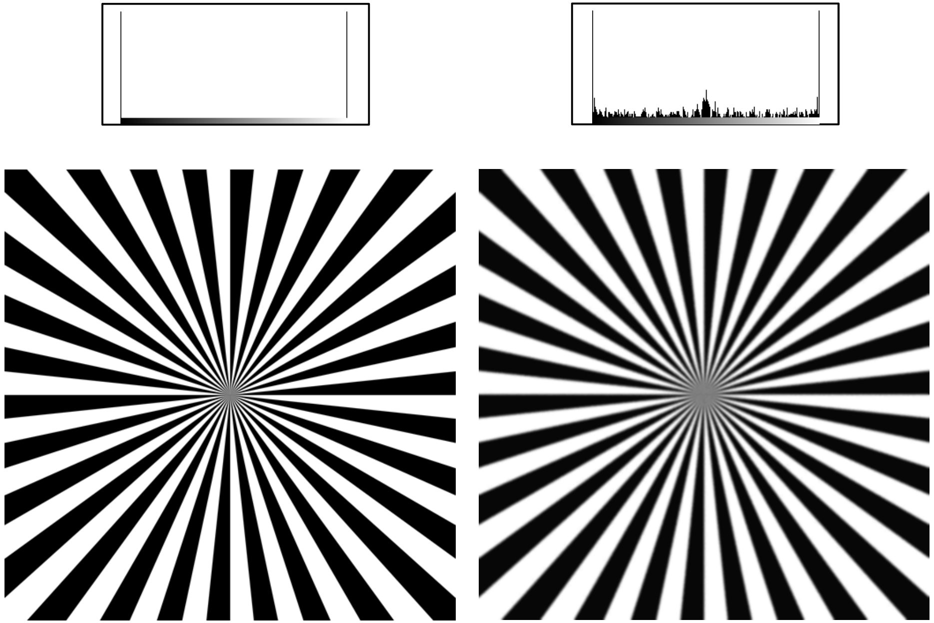
ANTI-ALIASING IN IMAGE PYRAMIDS



level 0

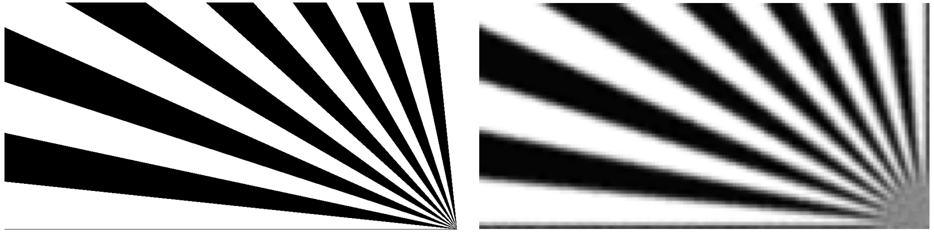


ANTI-ALIASING IN IMAGE PYRAMIDS

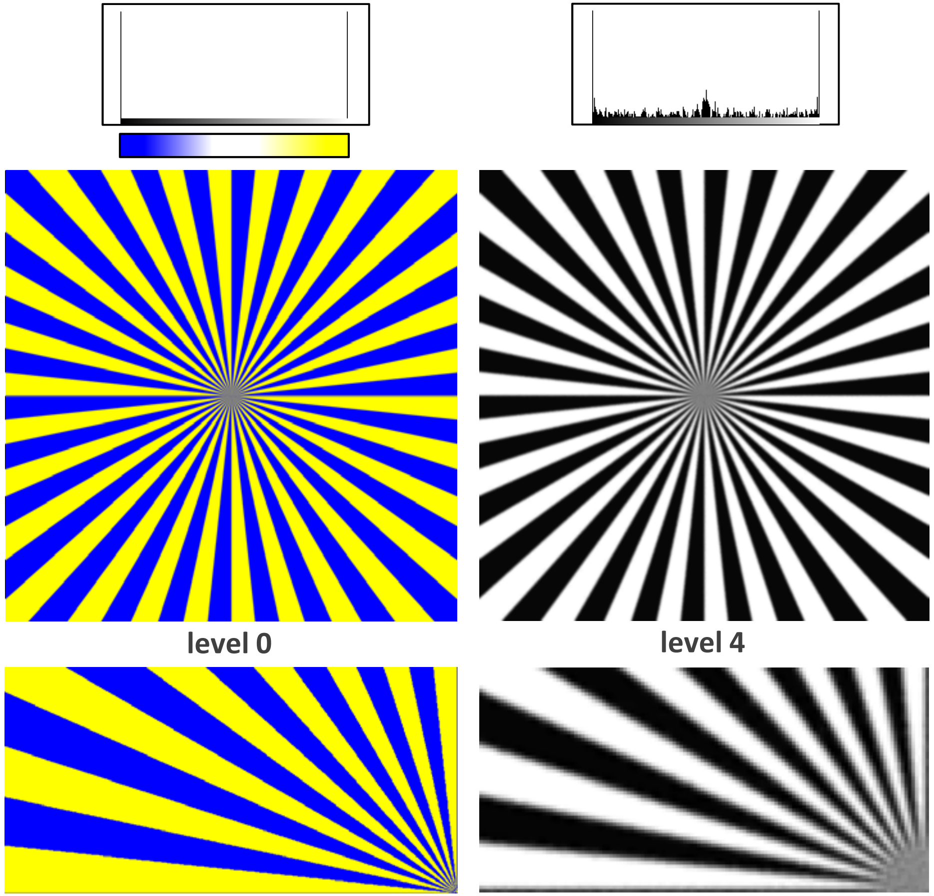


level 0

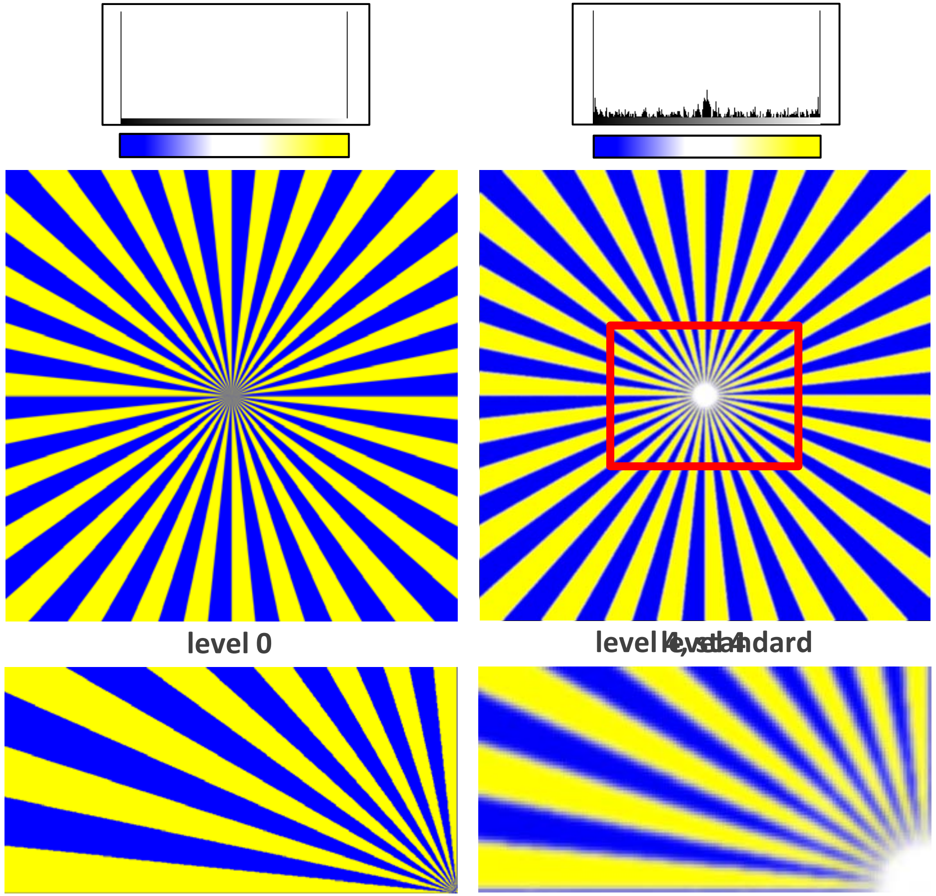
level 4



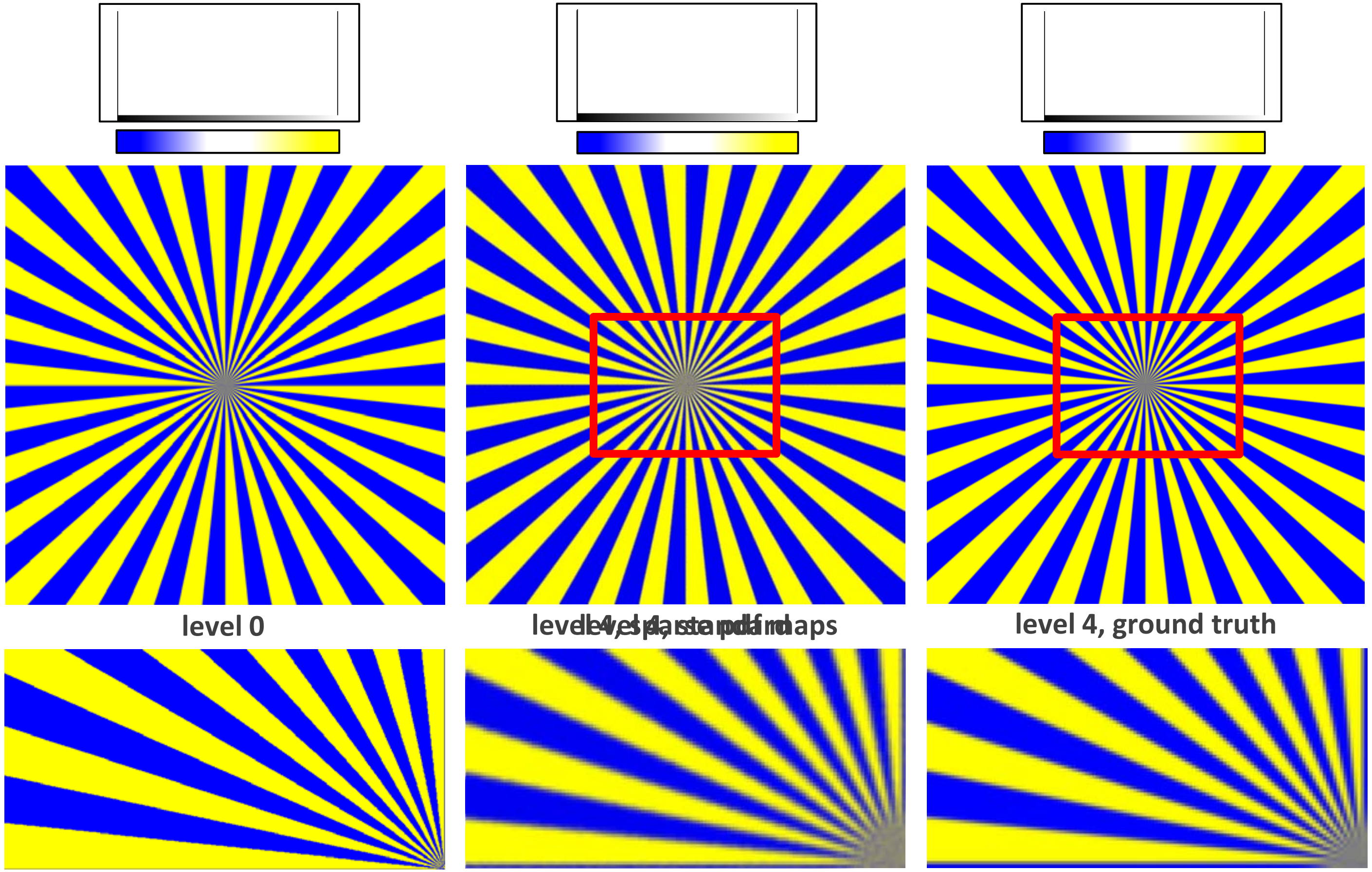
ANTI-ALIASING IN IMAGE PYRAMIDS



ANTI-ALIASING IN IMAGE PYRAMIDS



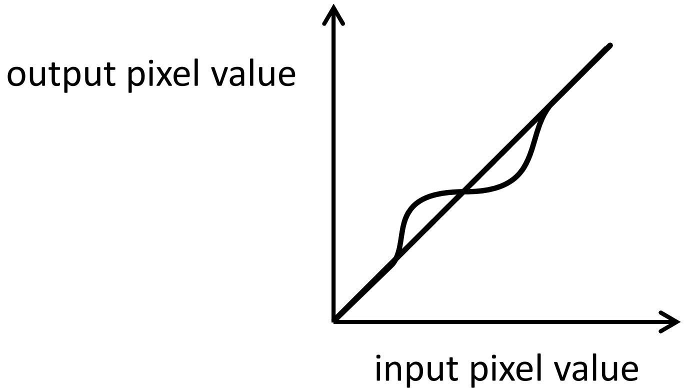
ANTI-ALIASING IN IMAGE PYRAMIDS



NON-LINEAR IMAGE OPERATORS

Apply non-linear operation to each pixel

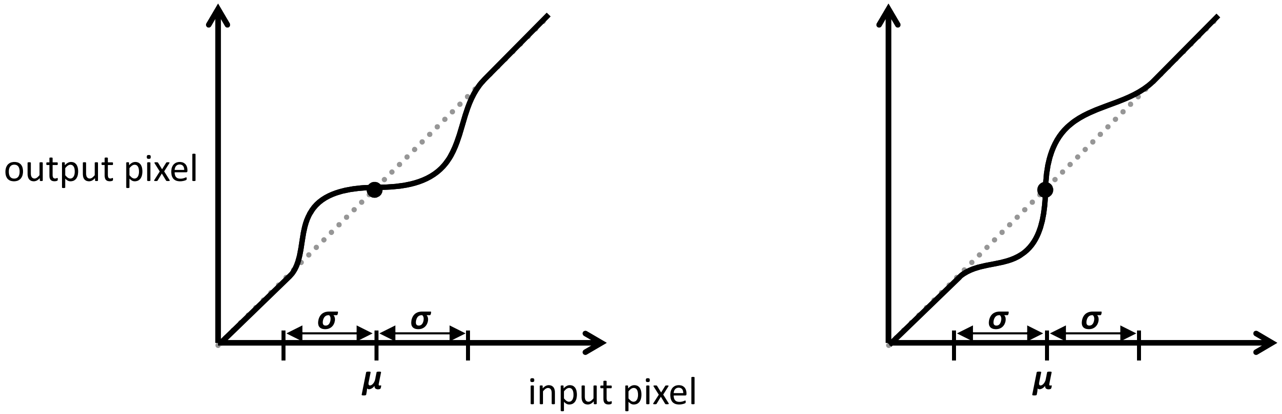
- Color map or non-linear contrast adjustment
- Bilateral filtering: range weight
- Smoothed local histogram filtering [Kass and Solomon 2010]
- Local Laplacian filtering [Paris et al. 2011]: point-wise, non-linear re-mapping



LOCAL LAPLACIAN FILTERING [PARIS ET AL. 2011]

Compute Laplacian pyramid coefficient

- Adjust local contrast via point-wise non-linearity; then downsample

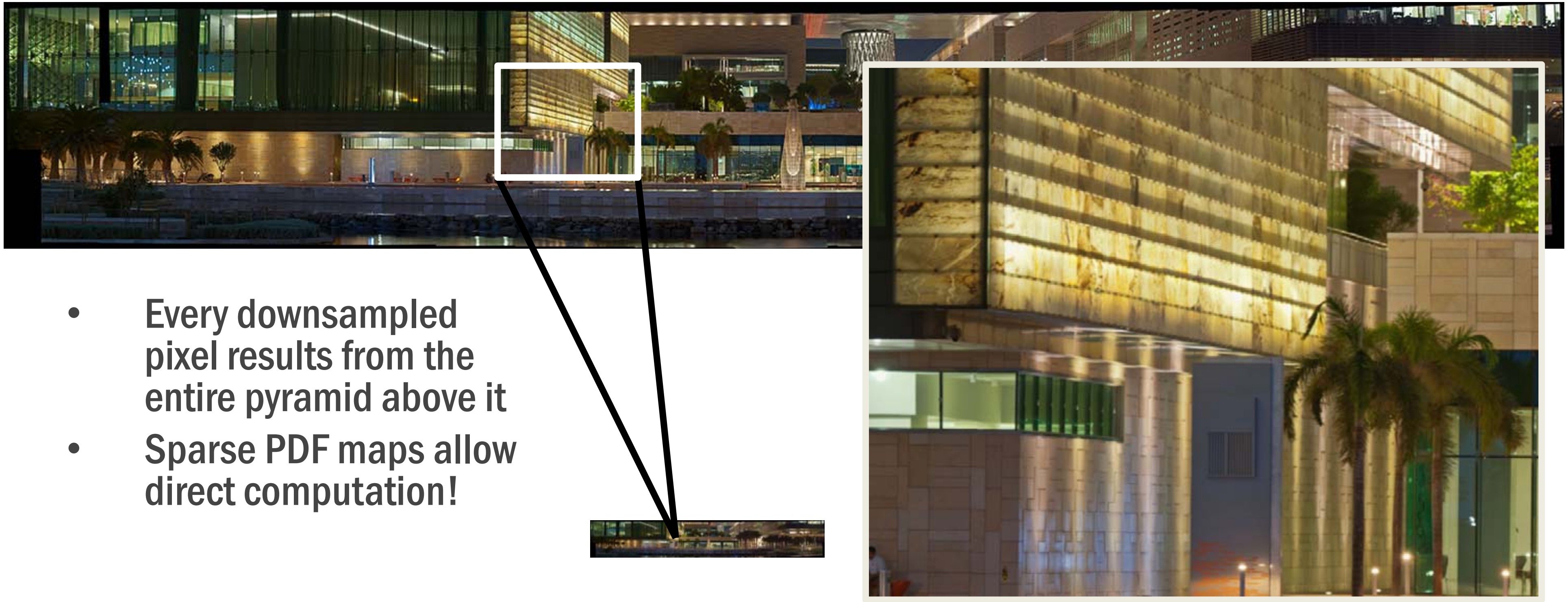


Same as local color mapping, then downsampling

- Cannot apply the re-mapping function to the downsampled image!
- Need to compute ground truth (pyramid!) or proper “anti-aliasing”

LOCAL LAPLACIAN FILTERING: SCALABILITY

Night Scene Panorama: 47,908 x 7,531 pixels (361 Mpixels)

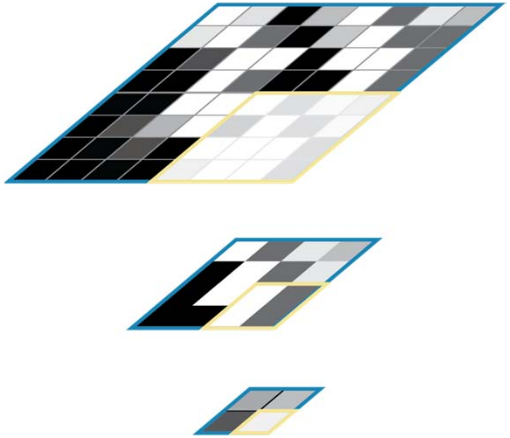


- Every downsampled pixel results from the entire pyramid above it
- Sparse PDF maps allow direct computation!

Sparse PDF Maps Concept

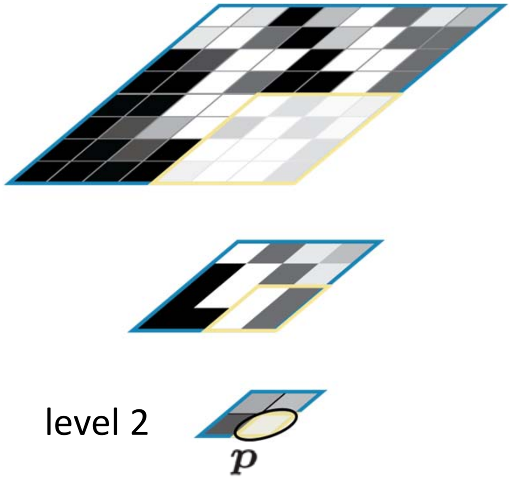
SPARSE PDF MAPS

Represent distribution of pixel values in footprint in original image



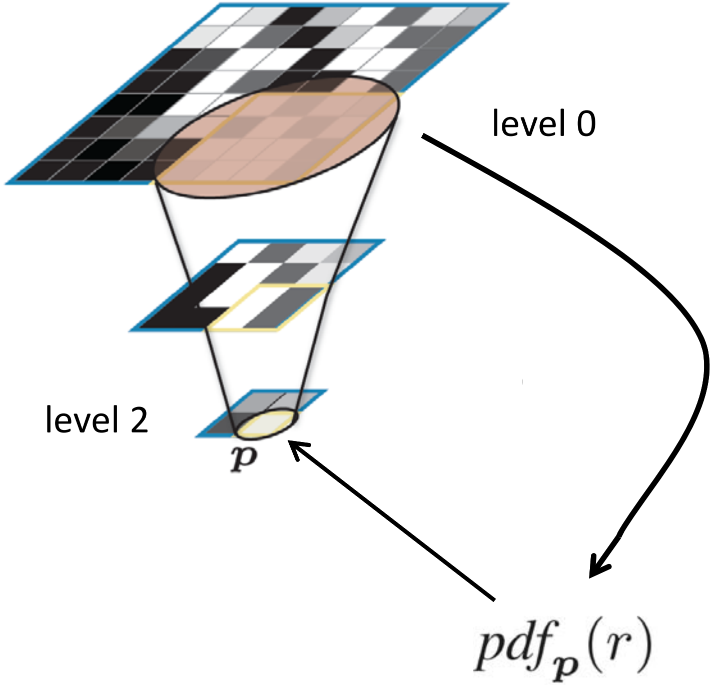
SPARSE PDF MAPS

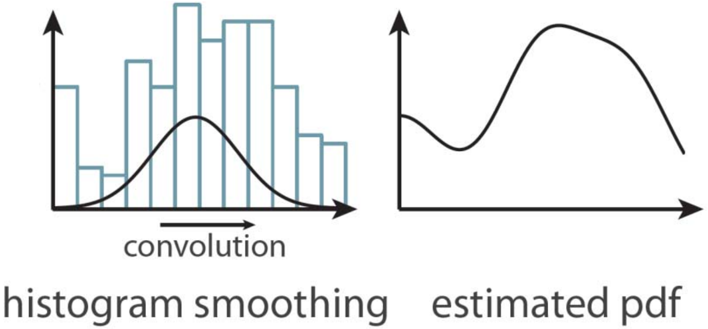
Represent distribution of pixel values in footprint in original image



SPARSE PDF MAPS

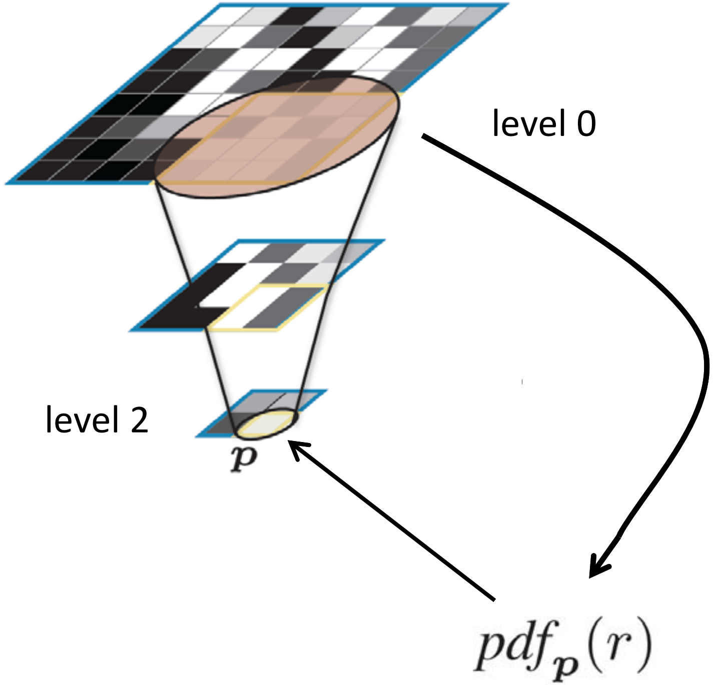
Represent distribution of pixel values in footprint in original image

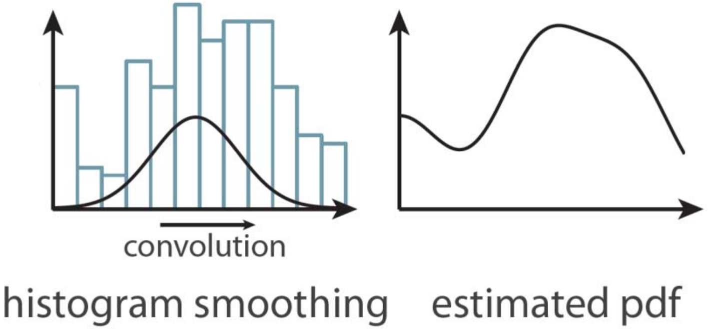




SPARSE PDF MAPS

Represent distribution of pixel values in footprint in original image





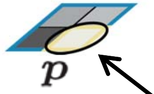
SIGGRAPH ASIA 2018 TOKYO

SPARSE PDF MAPS

Represent distribution of pixel values in footprint in original image

Apply non-linear operation

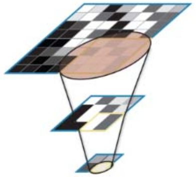
level 2



$$E\boxed{\left[t_{\boldsymbol{p}}\left(X_{\boldsymbol{p}}\right)\right]} = \frac{1}{w_{\boldsymbol{p}}}\int_0^1 \boxed{t_{\boldsymbol{p}}(r)}\boxed{pdf_{\boldsymbol{p}}(r)}\,dr$$

EXAMPLE 1: DOWN-SAMPLED IMAGE

$$E\left[t_{\boldsymbol{p}}\left(X_{\boldsymbol{p}}\right)\right] = \frac{1}{w_{\boldsymbol{p}}}\int_0^1 t_{\boldsymbol{p}}(r)pdf_{\boldsymbol{p}}(r)\;dr$$

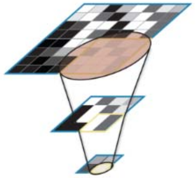


$$t_{\boldsymbol{p}}(r) = r$$

$$w_{\boldsymbol{p}} = 1$$

EXAMPLE 2: COLOR MAPPING

$$E\left[t_{\boldsymbol{p}}\left(X_{\boldsymbol{p}}\right)\right] = \frac{1}{w_{\boldsymbol{p}}}\int_0^1 t_{\boldsymbol{p}}(r)pdf_{\boldsymbol{p}}(r)\ dr$$

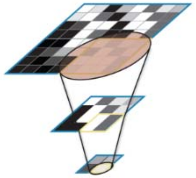


$t_{\boldsymbol{p}}(r) =$ color map

$$w_{\boldsymbol{p}} = 1$$

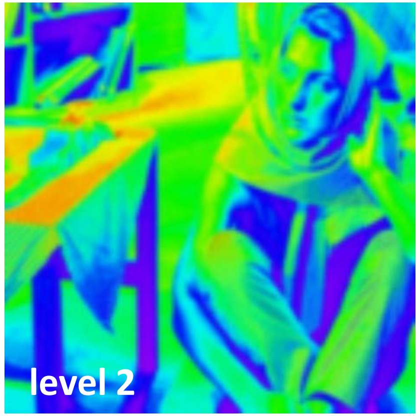
EXAMPLE 2: COLOR MAPPING

$$E\left[t_{\mathbf{p}}\left(X_{\mathbf{p}}\right)\right] = \frac{1}{w_{\mathbf{p}}} \int_0^1 t_{\mathbf{p}}(r) pdf_{\mathbf{p}}(r)\, dr$$



$$t_{\mathbf{p}}(r) = \text{color map}$$

$$w_{\mathbf{p}} = 1$$

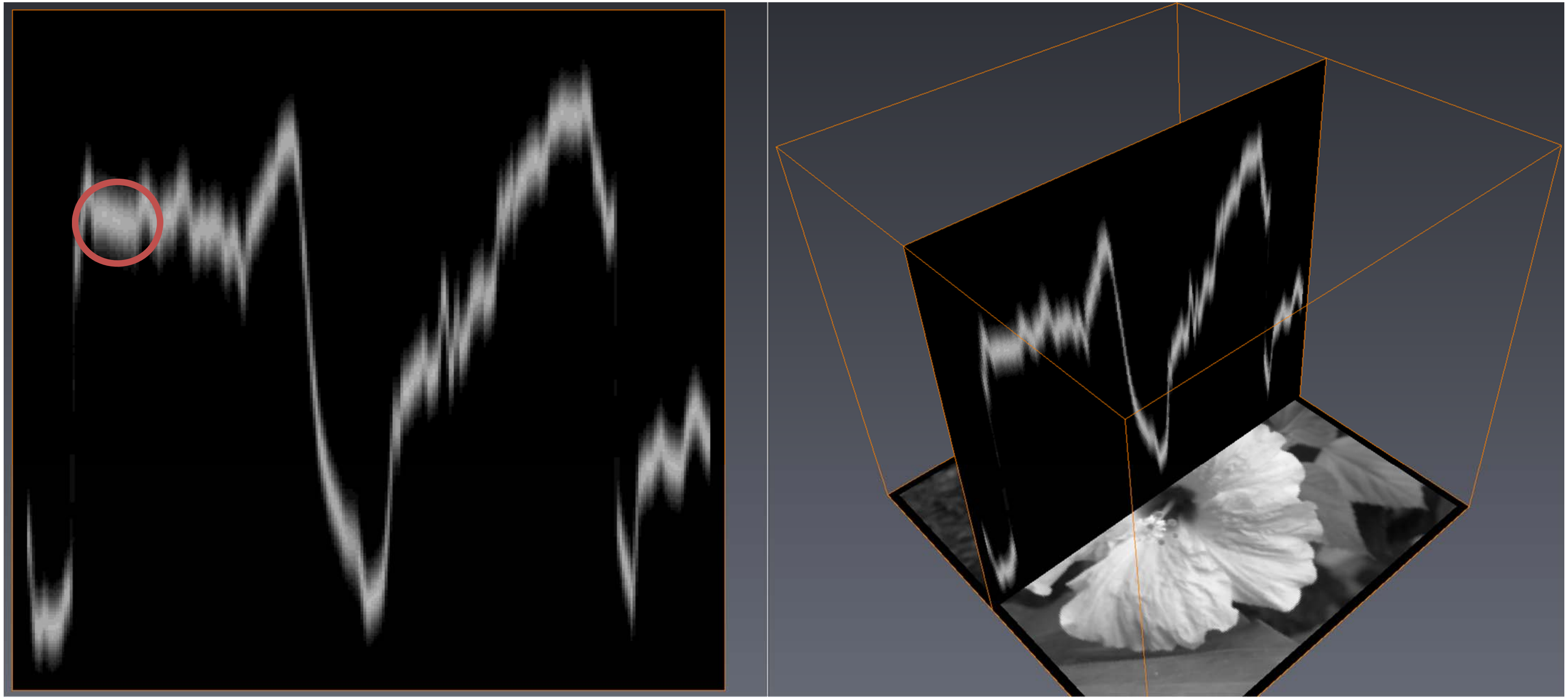


plus: bilateral filtering, local Laplacian filtering in linear time, …

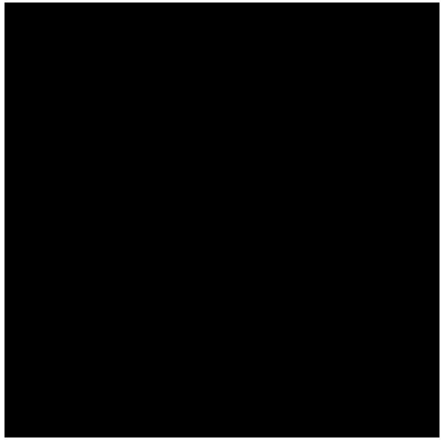
INTERACTIVE GIGAPIXEL FILTERING

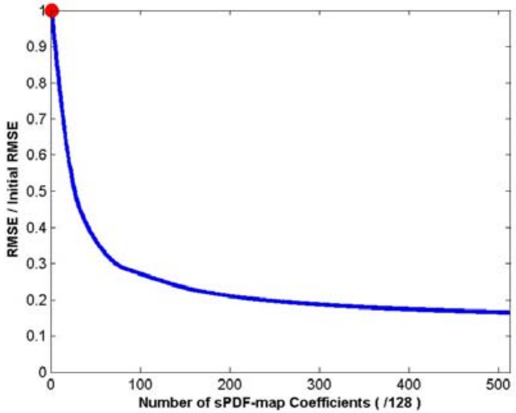
Computation

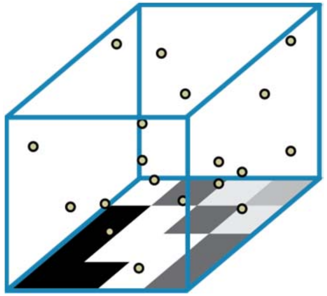
SPATIAL AND RANGE COHERENCE



GREEDY APPROXIMATION: MATCHING PURSUIT





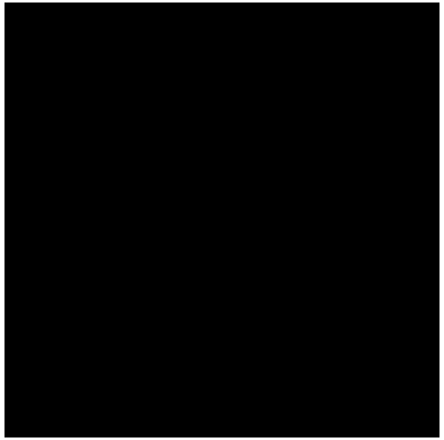


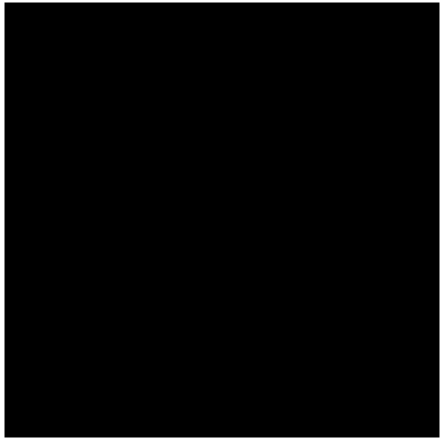
Spatial filter W: 5 x 5

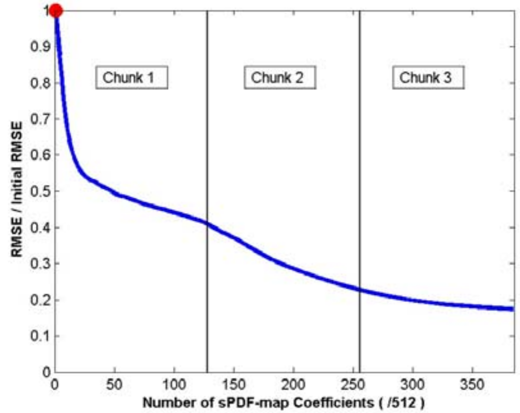
1 coefficient chunk

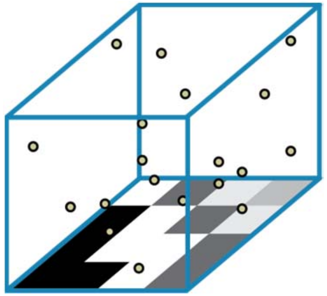
(# coefficients == 1 * # pixels)

GREEDY APPROXIMATION: MATCHING PURSUIT







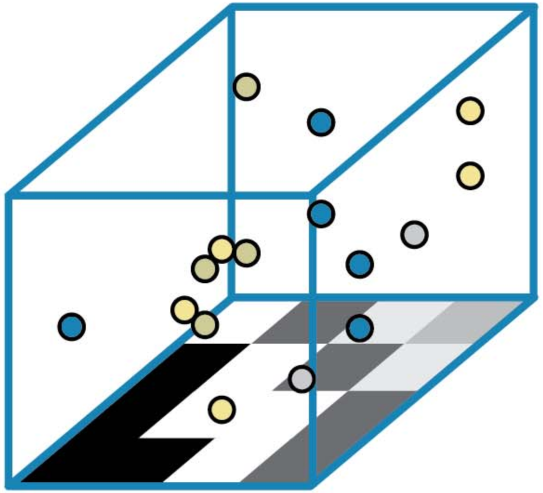


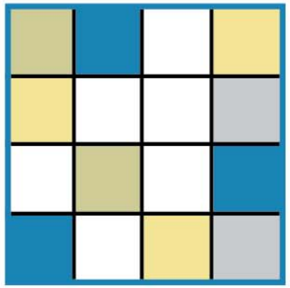
Spatial filter W: 3 x 3

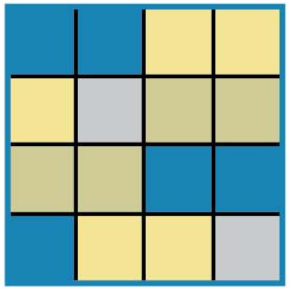
1-3 coefficient chunks
(# coefficients == 1-3 * # pixels)

Data Structure

SPDF MAPS DATA STRUCTURE

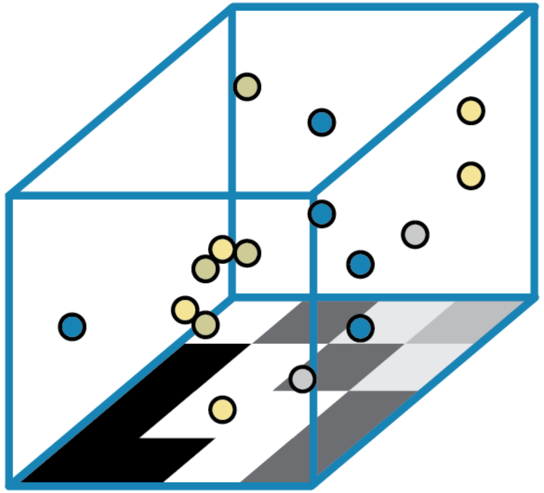






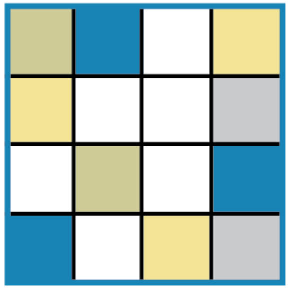
conceptual	index image	coefficient image
$V(\boldsymbol{p}_n, r_n) = c_n$	$(index, count)_{\boldsymbol{p}}$	(r_n, c_n)

SPDF MAPS DATA STRUCTURE



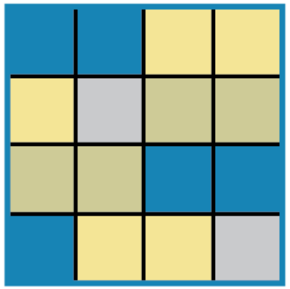
conceptual

$$V(\boldsymbol{p}_n, r_n) = c_n$$



index image

$$(index, count)_{\boldsymbol{p}}$$



coefficient image

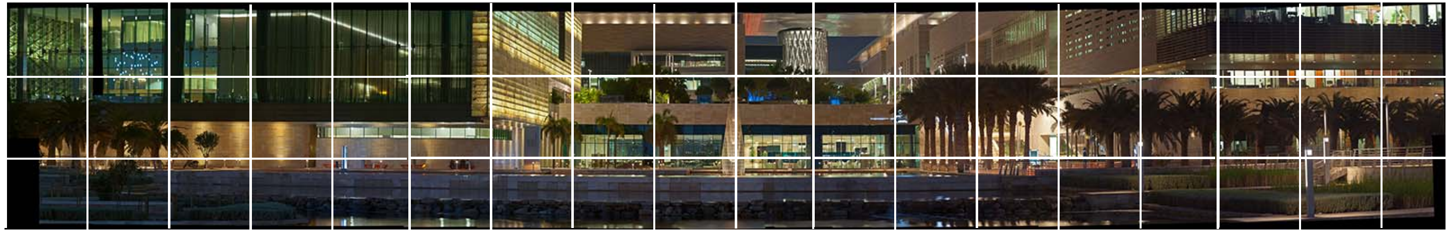
$$(r_n, c_n)$$

Display-Aware Gigapixel Image Processing

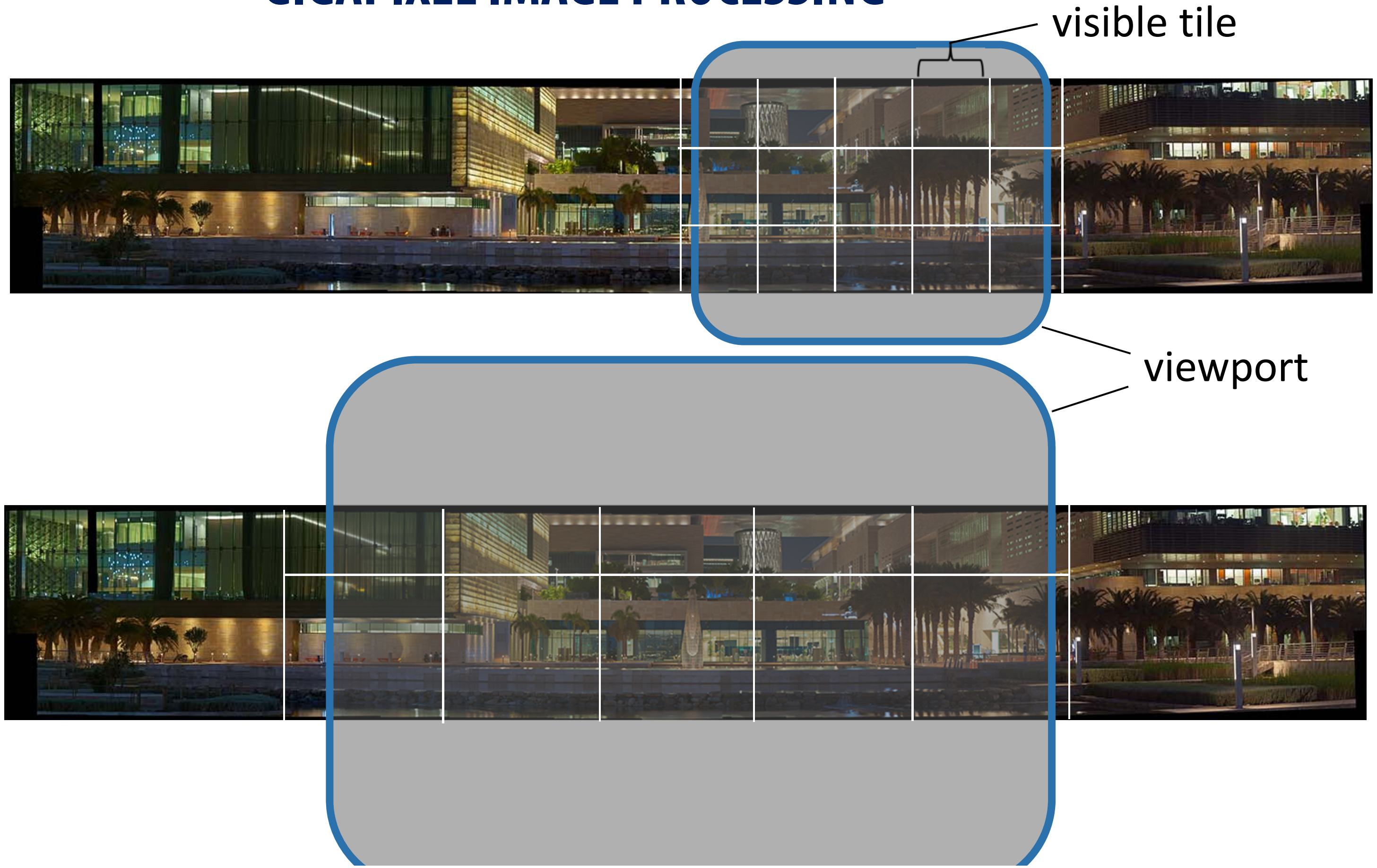
GIGAPIXEL IMAGE PROCESSING

Out-of-Core Processing

- Divide data into smaller tiles, process each tile independently (e.g., 256x256)
- Image operations are performed only on requested sub-tiles (display-aware)
- Rendering based on tiled data, using GPU-based virtual memory approach

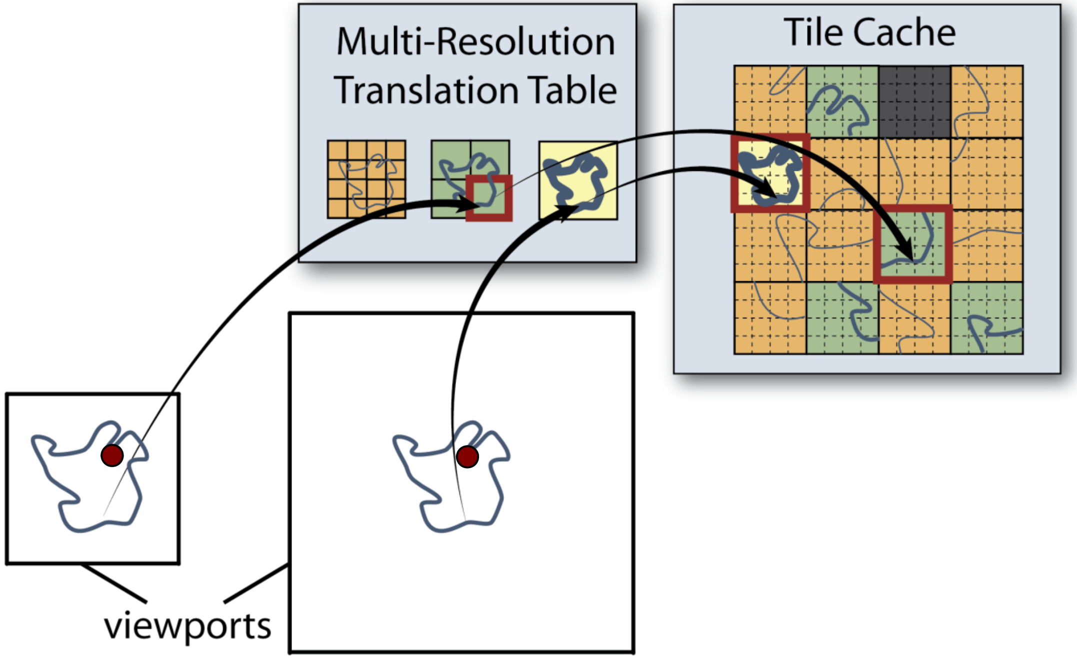


GIGAPIXEL IMAGE PROCESSING



GIGAPIXEL IMAGE PROCESSING

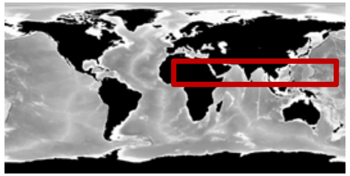
GPU-based virtual memory architecture [Hadwiger et al. 2012]

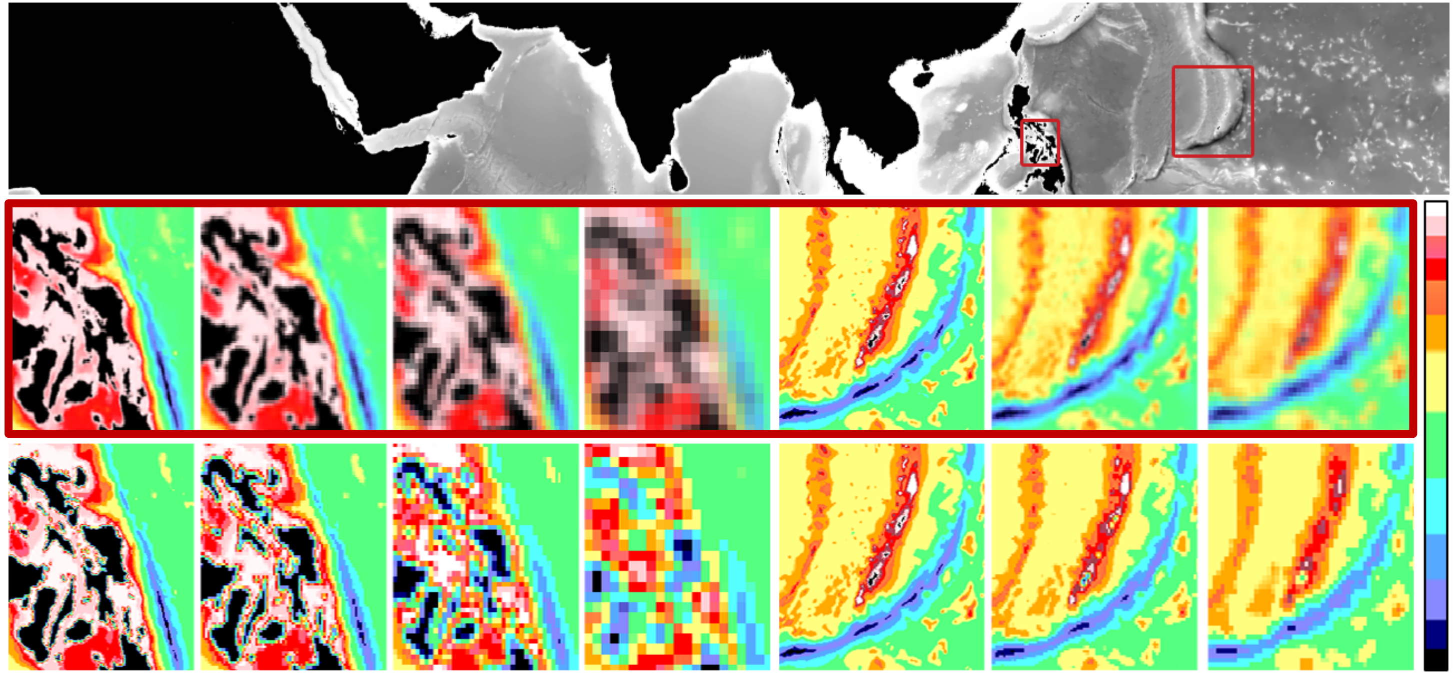


Results

COLOR MAPPING GIGAPIXEL IMAGES

NASA Blue Marble bathymetry: 21,601 x 10,801 pixels (233 Mpixels)






details enhanced
original
details reduced
details enhanced
original
details reduced

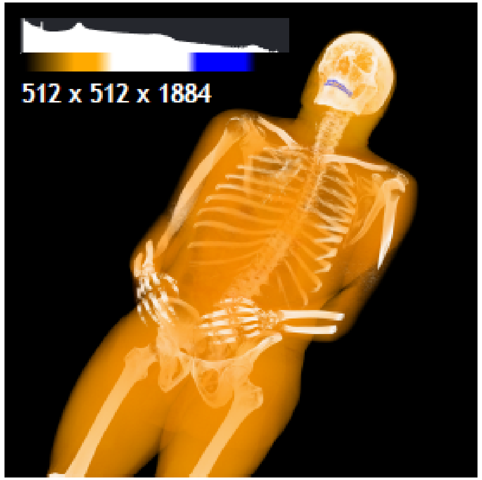
GIGAPIXEL LOCAL LAPLACIAN FILTERING


original


details reduced

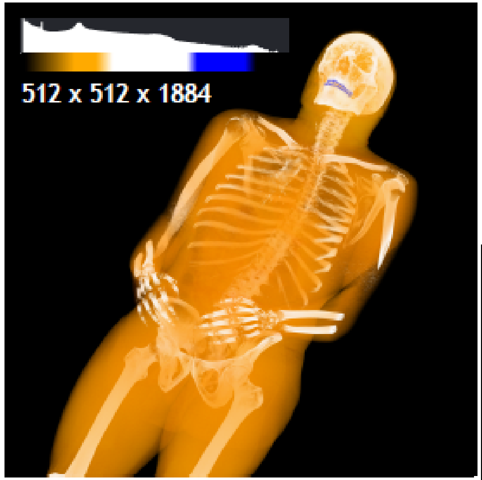

details enhanced

VISIBLE HUMAN (512 X 512 X 1884)



original volume

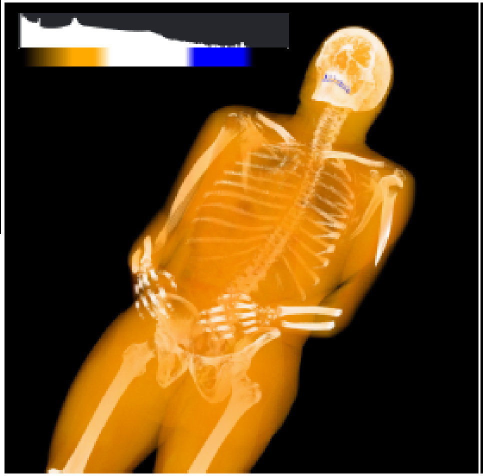
VISIBLE HUMAN (512 X 512 X 1884)

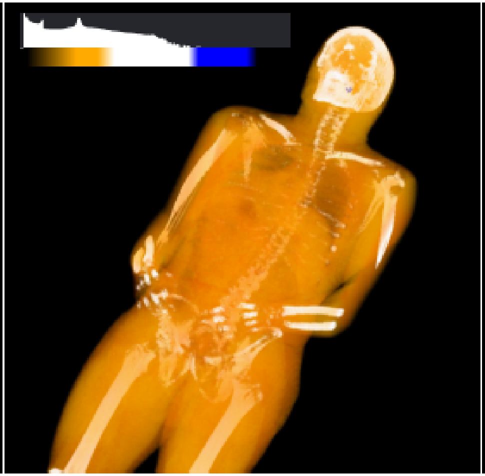


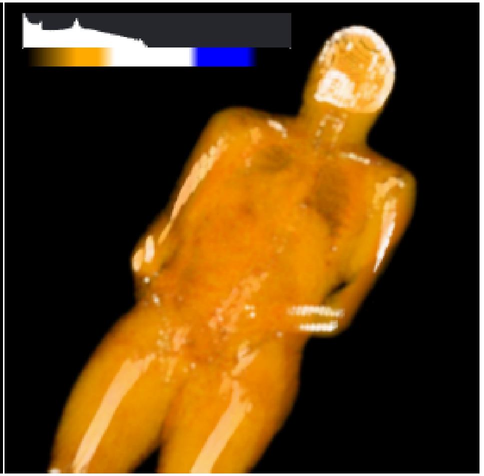
original volume

fine to coarse →

octree (averaging) →



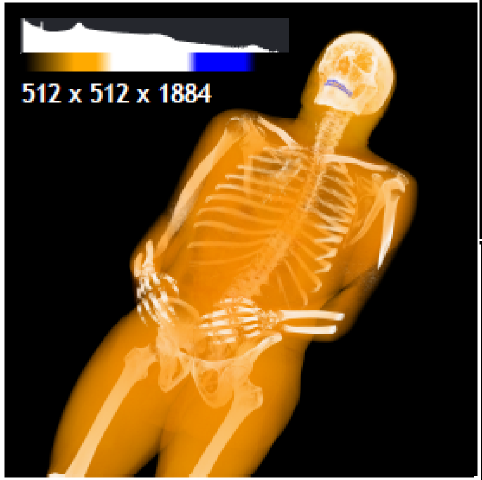




SIGGRAPH ASIA 2018 TOKYO

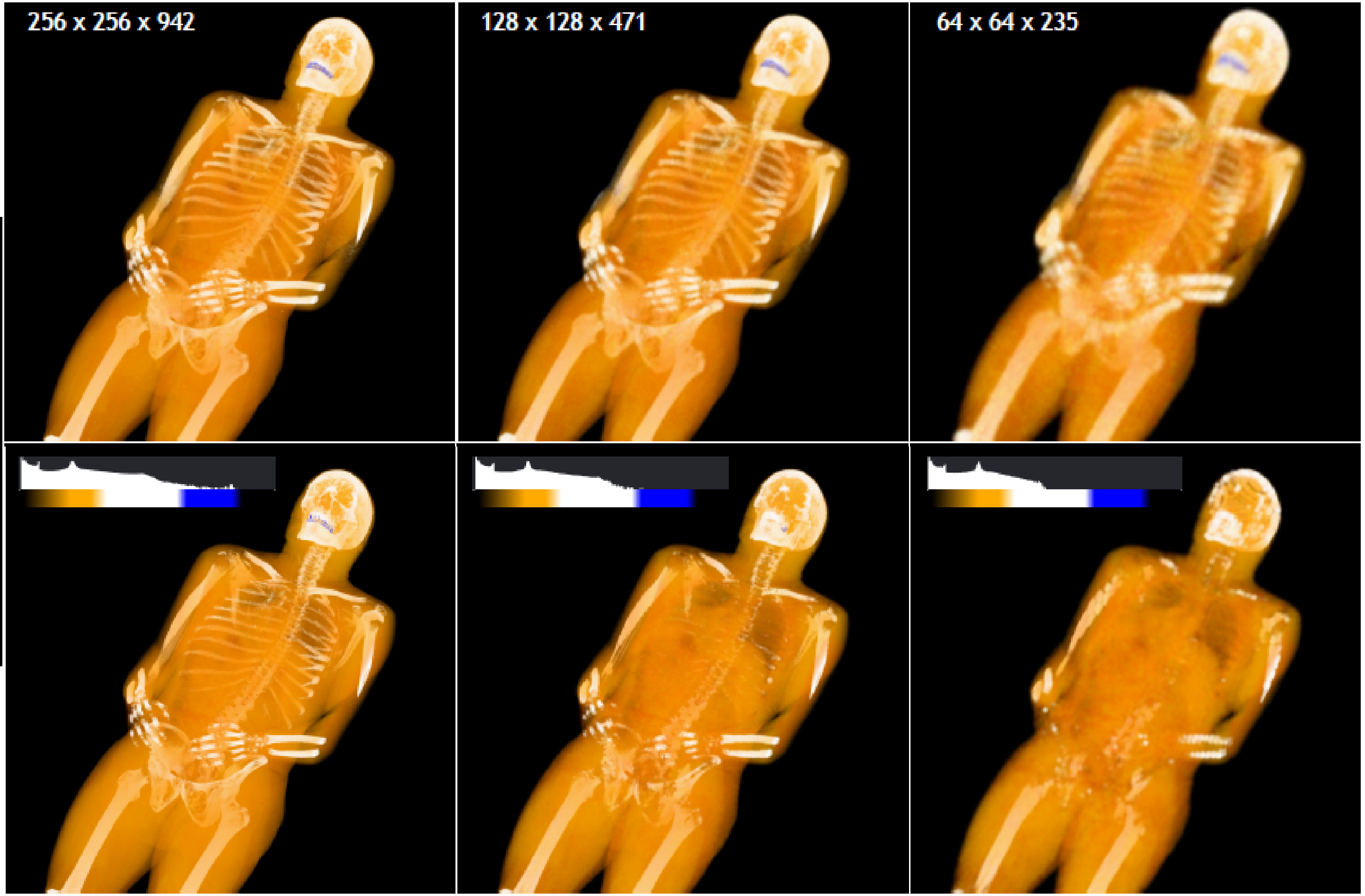
VISIBLE HUMAN (512 X 512 X 1884)

sparse pdf volumes →



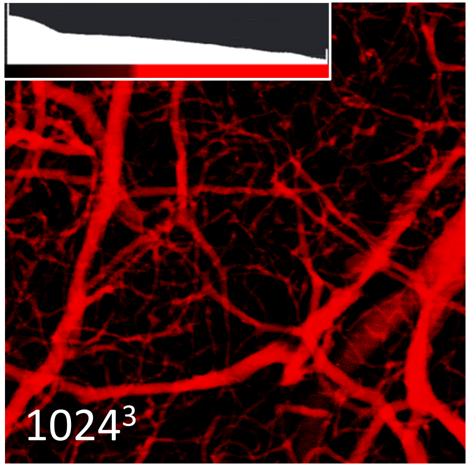
original volume

octree (averaging) →



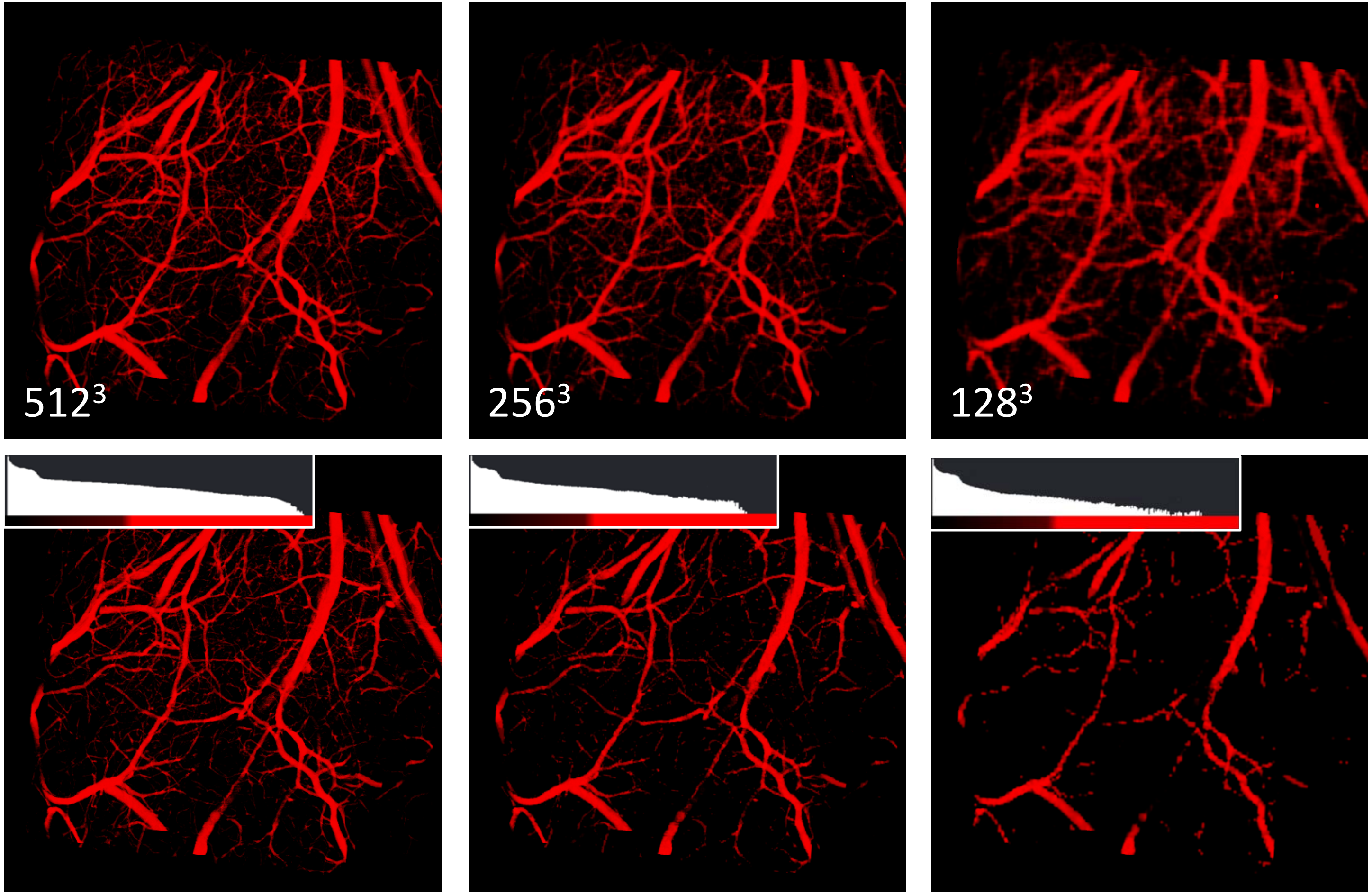
BLOOD VESSELS (1024 X 1024 X 1024)

sparse pdf volumes →



original volume

octree (averaging) →



SUMMARY

Display-aware processing with flexible new image pyramid (spdf map)

- Consistent, sparse representation of pixel footprint pdfs

Unified evaluation of many important non-linear image operations

- Local Laplacian filtering for gigapixel images

Efficient CUDA implementation

- Pre-computation costly, but only performed once
- Run time storage and computation similar to standard pyramids

Sparse PDF maps for images:
Hadwiger et al., Sparse PDF Maps for Non-Linear Multi-Resolution Image Operations, Siggraph Asia 2012

Sparse PDF volumes for volume rendering:
Sicat et al., Sparse PDF Volumes for Consistent Multi-Resolution Volume Rendering, IEEE Scientific Visualization 2014

SIGGRAPH ASIA 2018 TOKYO

CONFERENCE 4 – 7 December 2018
EXHIBITION 5 – 7 December 2018
Tokyo International Forum, Japan
SA2018.SIGGRAPH.ORG

Sponsored by

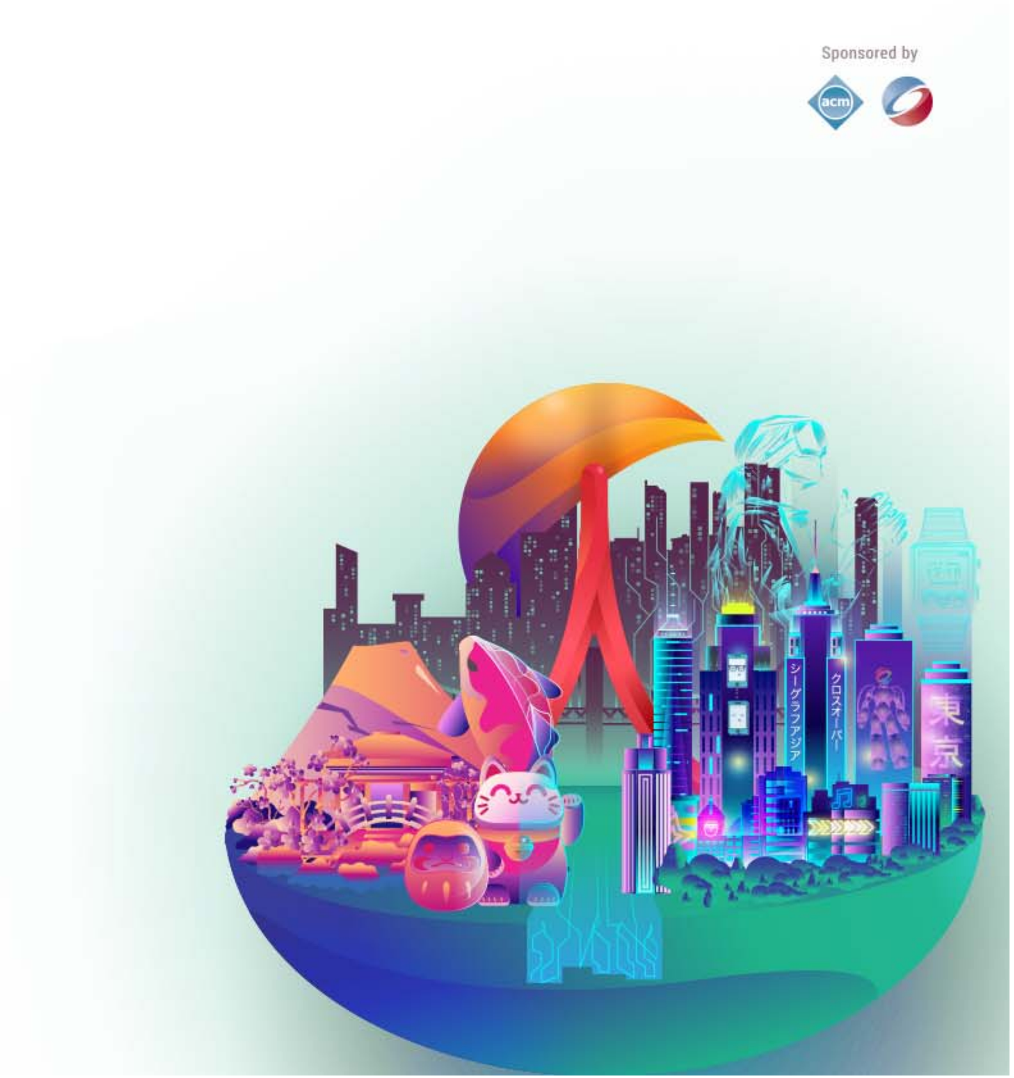
GPU-Based Large-Scale Scientific Visualization

Johanna Beyer, Harvard University

Markus Hadwiger, KAUST

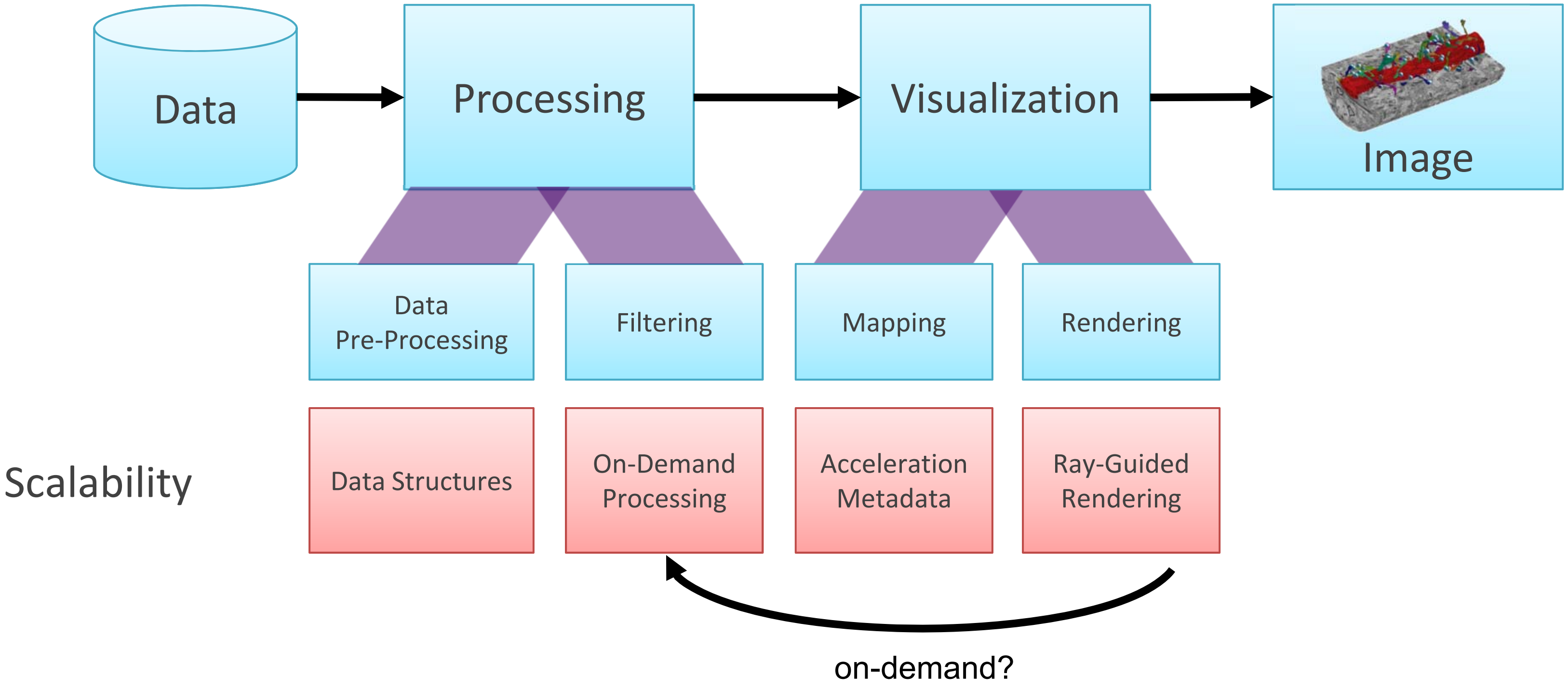
Course Website:

http://johanna-b.github.io/LargeSciVis2018/index.html



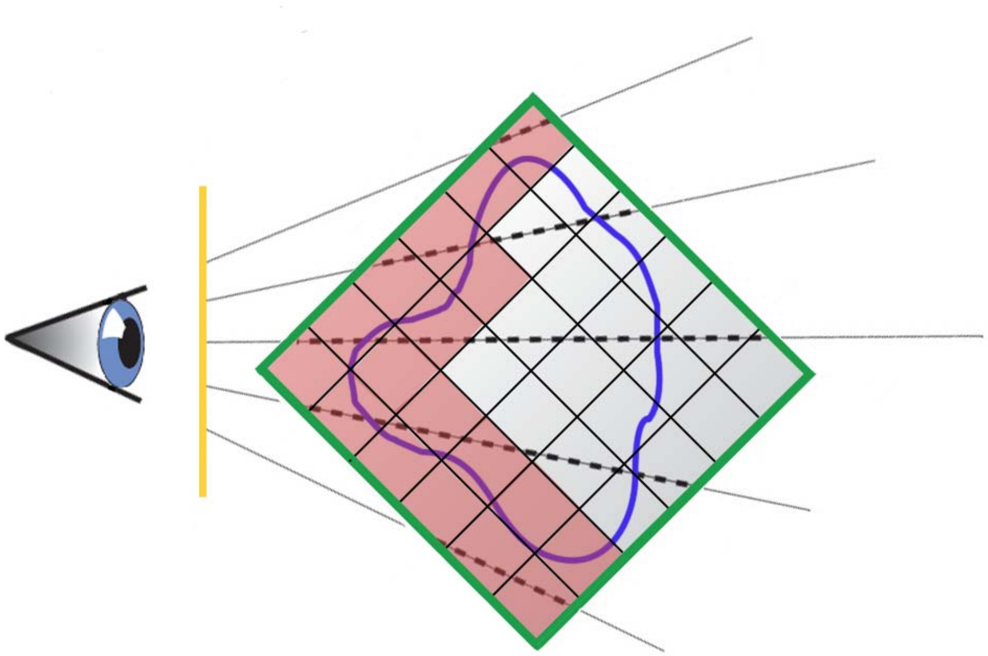
Wrap-Up, Summary

LARGE-SCALE VISUALIZATION PIPELINE



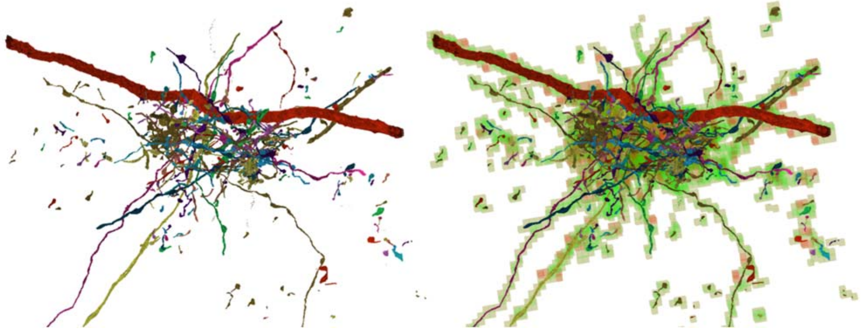
RAY-GUIDED VOLUME RENDERING

- Working set determination on GPU
- Single-pass rendering
- Traversal on GPU
- Virtual texturing



VOLUME RENDERING OF SEGMENTED DATA

- Empty space skipping essential
- Efficient culling is basis for empty space skipping
  - Compact and scalable data structure (to millions of objects)
  - Hierarchical culling algorithm
- Hybrid approaches
  - Image-order vs. object-order
  - Deterministic vs. probabilistic



Sponsored by

SIGGRAPH ASIA 2018 TOKYO

CONFERENCE 4 – 7 December 2018
EXHIBITION 5 – 7 December 2018
Tokyo International Forum, Japan
SA2018.SIGGRAPH.ORG

THANK YOU!

Johanna Beyer, Harvard University
Markus Hadwiger, KAUST

Course Website:
http://johanna-b.github.io/LargeSciVis2018/index.html