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

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DISPLAY-AWARE IMAGE OPERATIONS

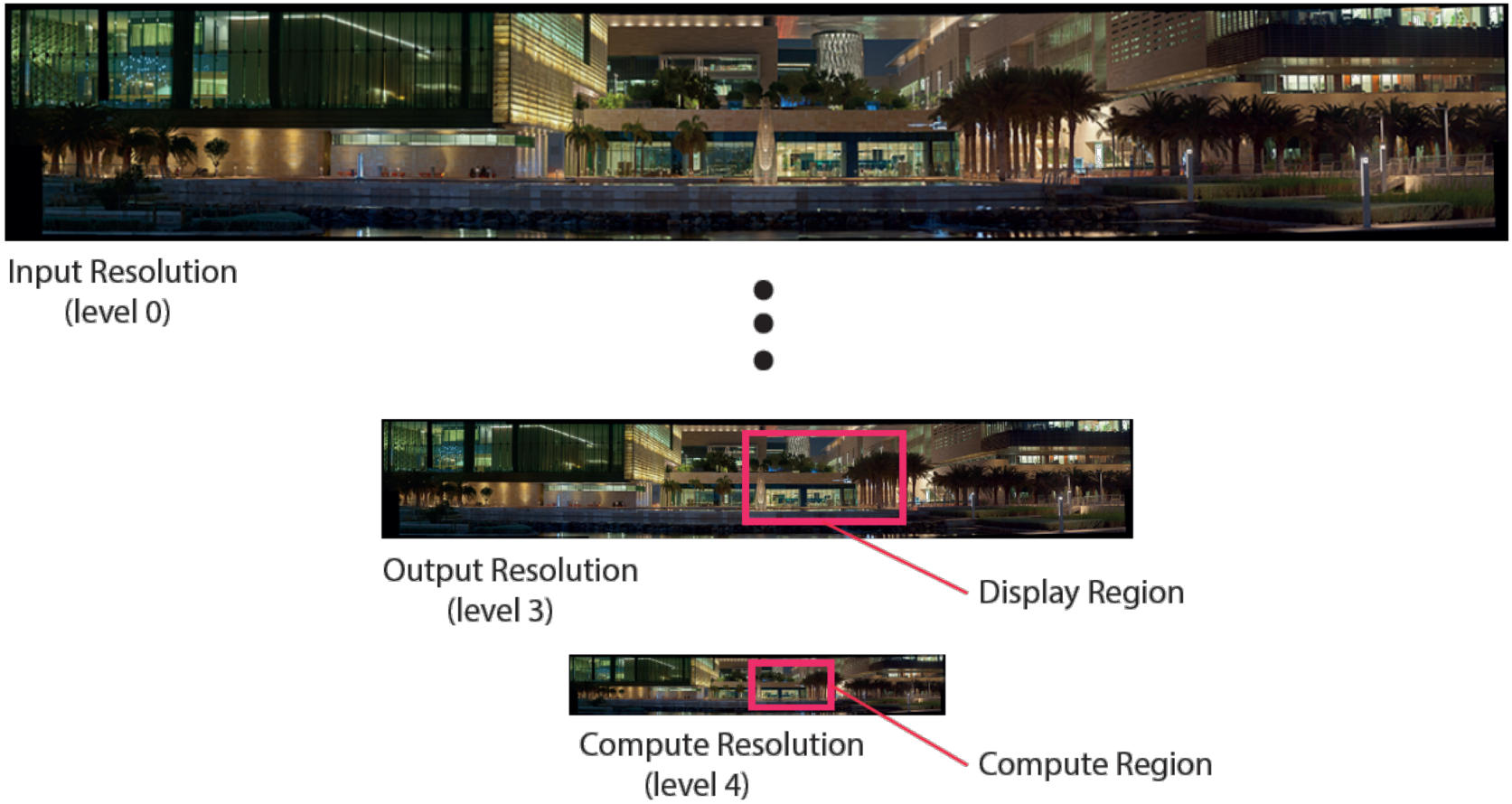

IMAGE PYRAMIDS

- 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

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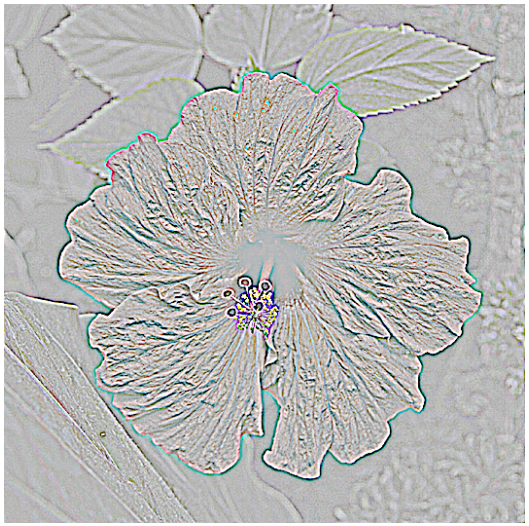

level 0

level 1

level 2

level 3

IMAGE PYRAMIDS

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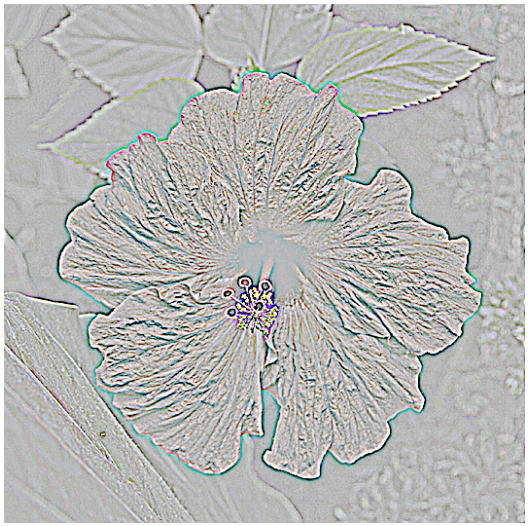

level 0

level 1

level 2

level 3

IMAGE PYRAMIDS

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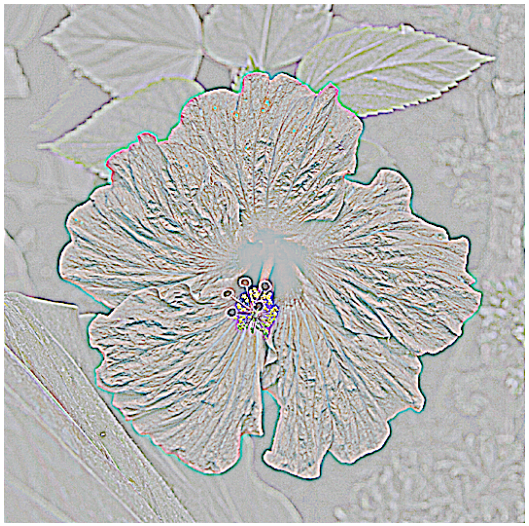
  - Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression
  - Sparse pdf maps [Hadwiger et al. 2012]



level 0

Laplacian pyramid

level 1

level 2

level 3

IMAGE PYRAMIDS

- Dyadic image pyramids
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  - Gaussian/Laplacian pyramids [Burt and Adelson 1983]: image processing/compression
  - Sparse pdf maps [Hadwiger et al. 2012]

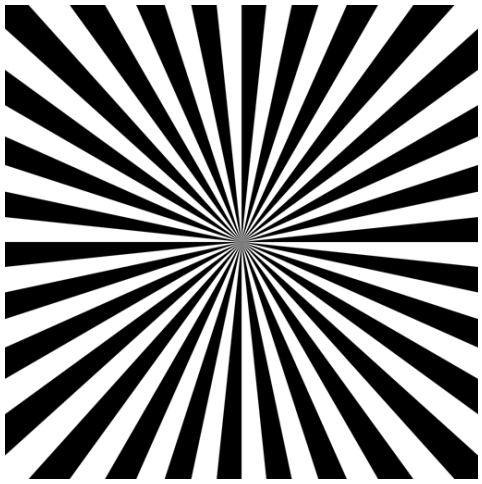
level 0

level 1

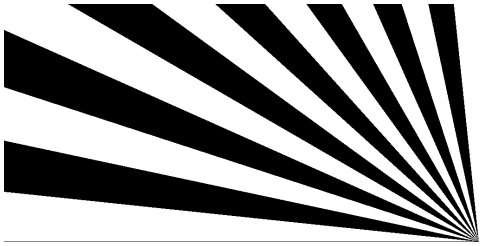
level 2

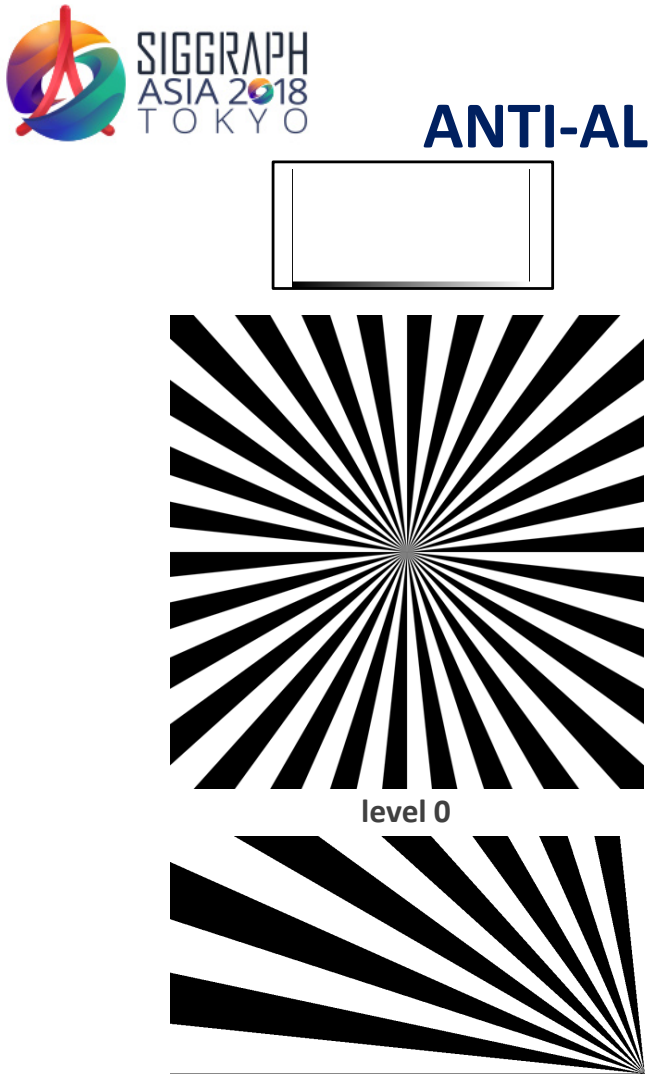
level 3

ANTI-ALIASING IN IMAGE PYRAMIDS



level 0





ANTI-ALIASING IN IMAGE PYRAMIDS

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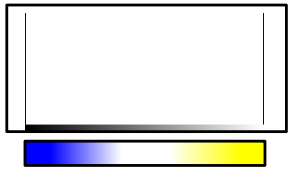
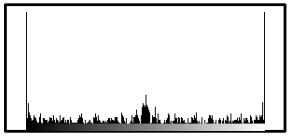
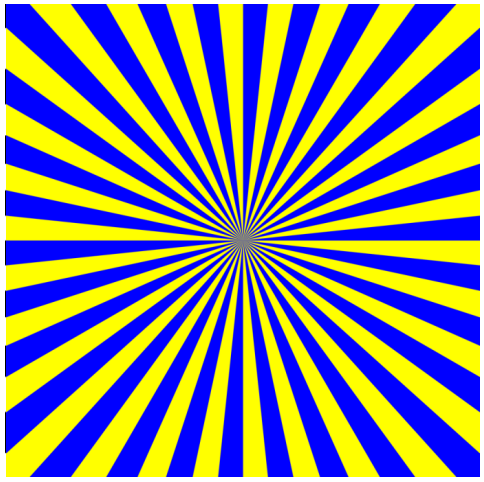
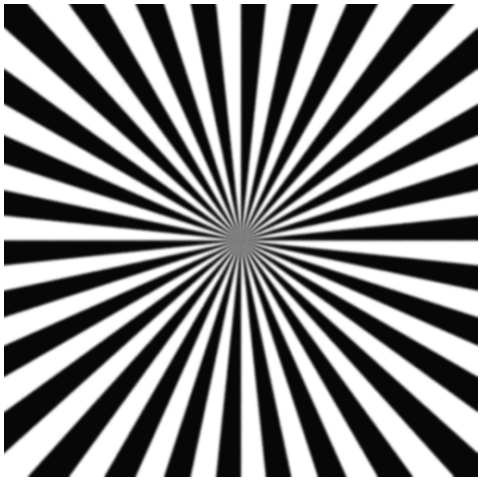


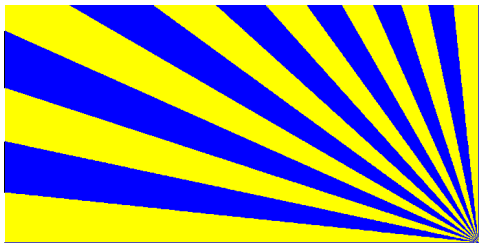




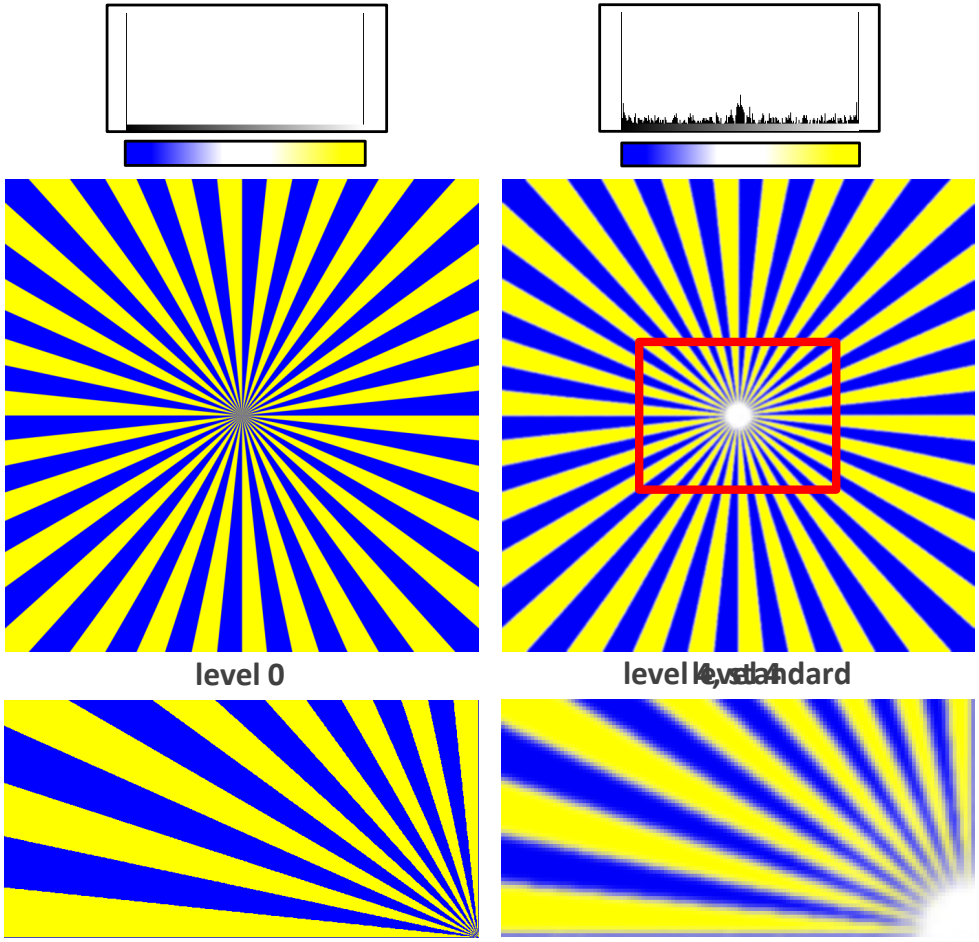
level 0



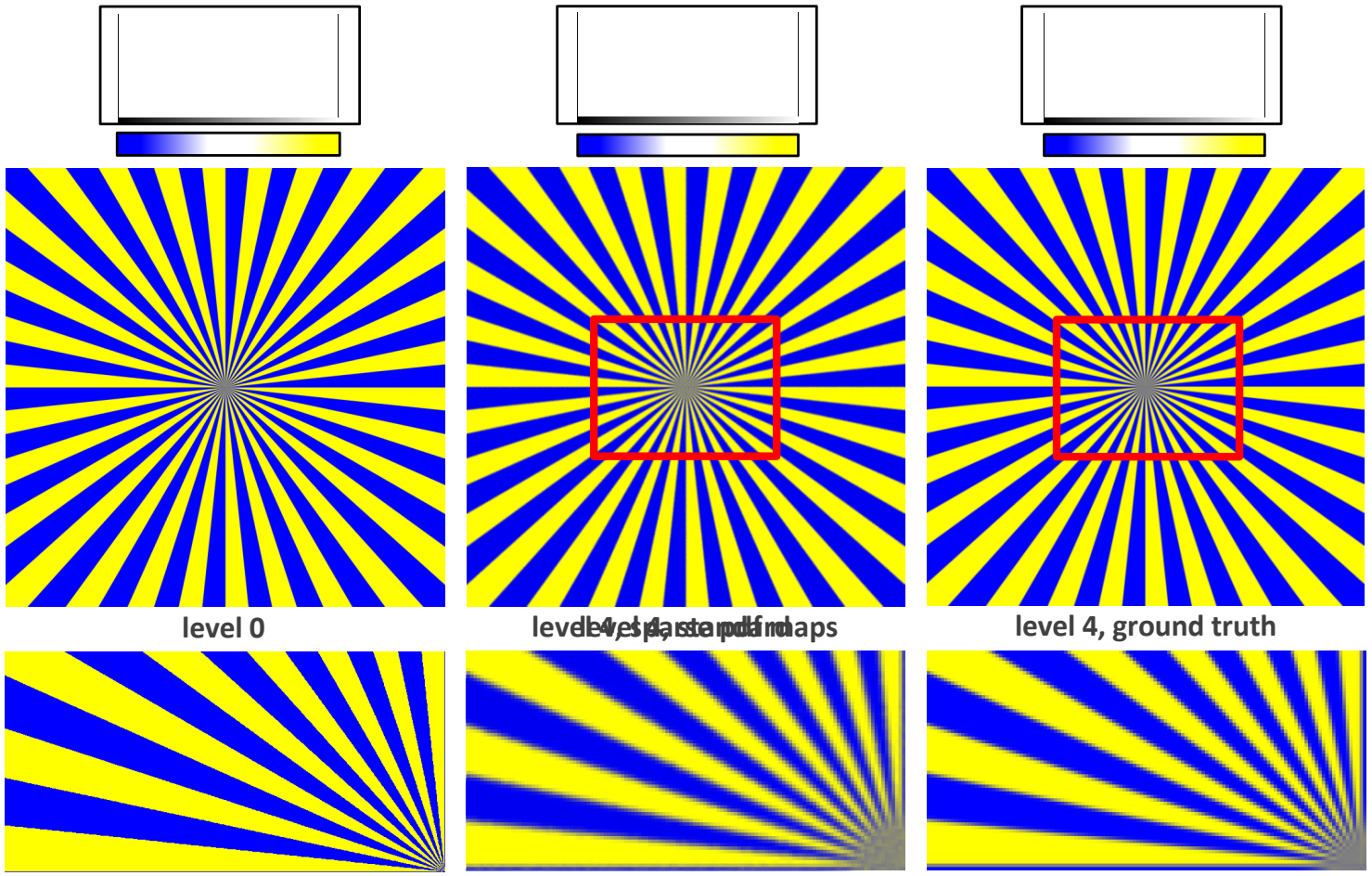
level 4



ANTI-ALIASING IN IMAGE PYRAMIDS



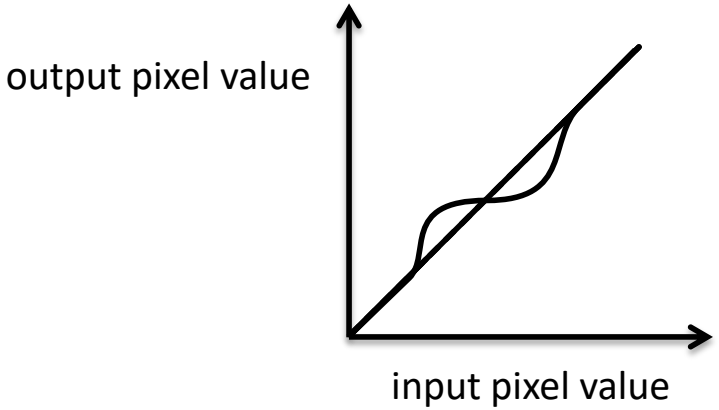
ANTI-ALIASING IN IMAGE PYRAMIDS



NON-LINEAR IMAGE OPERATORS

Apply non-linear operation to each pixel

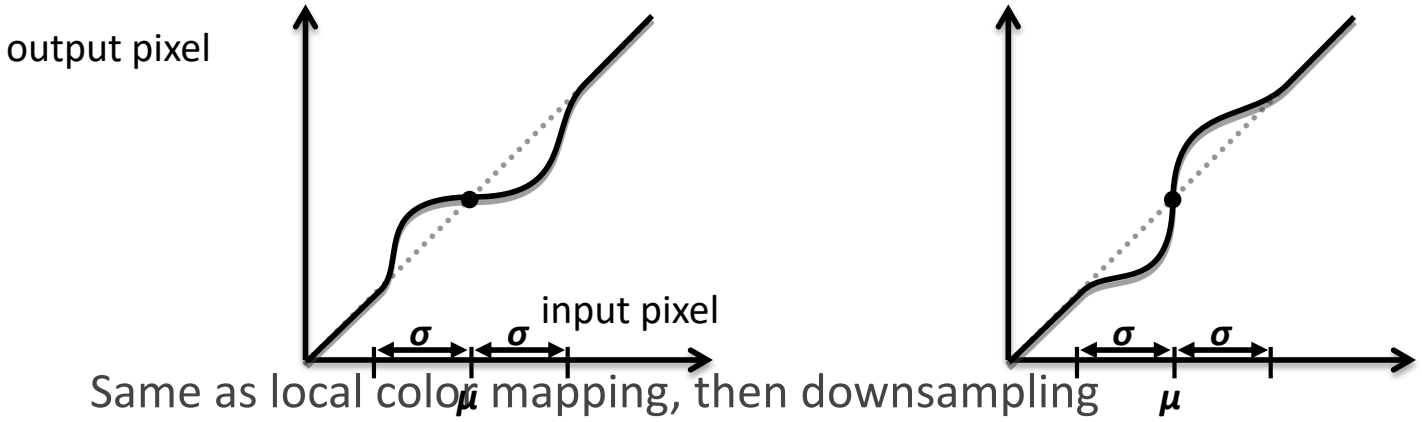
- Color map or non-linear contrast adjustment
- Bilateral filtering: range weight
- Smoothed local histogram filtering [Kass and Solomon 2010]
- Local Laplacian filtering [Paris et al. 2011]: point-wise, non-linear re-mapping



LOCAL LAPLACIAN FILTERING [PARIS ET AL. 2011]

Compute Laplacian pyramid coefficient

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

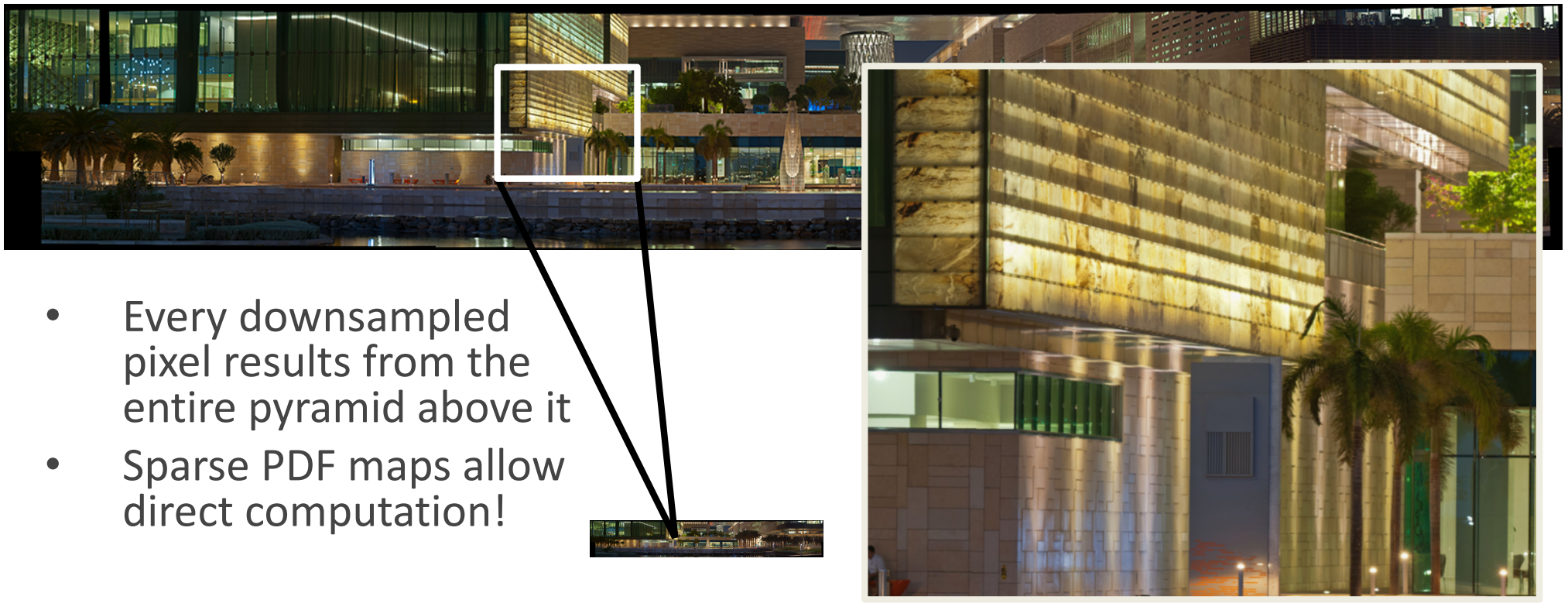


Same as local color mapping, then downsampling

- 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)

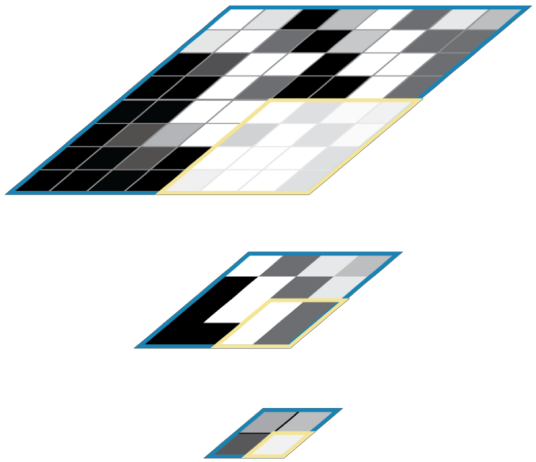


- Every downsampled pixel results from the entire pyramid above it
- Sparse PDF maps allow direct computation!

Sparse PDF Maps: Concept

SPARSE PDF MAPS

Represent distribution of pixel values in footprint in original image



SPARSE PDF MAPS

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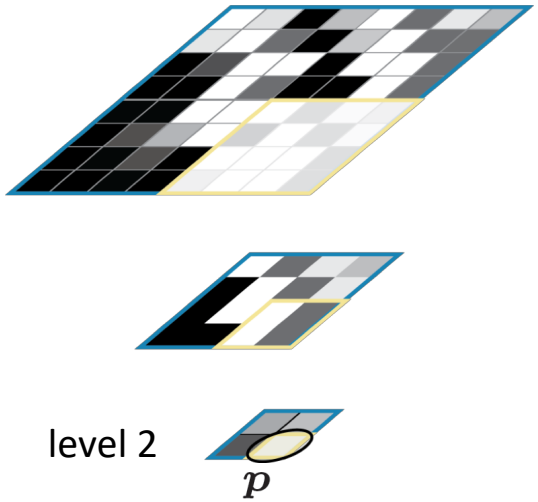

SPARSE PDF MAPS

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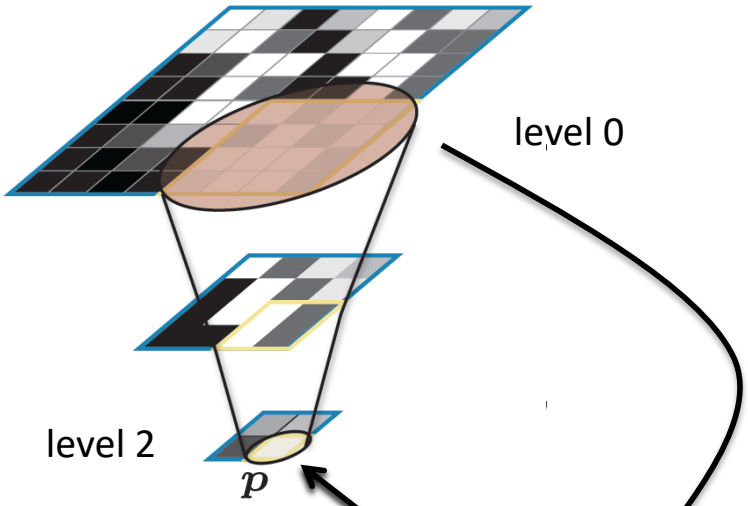
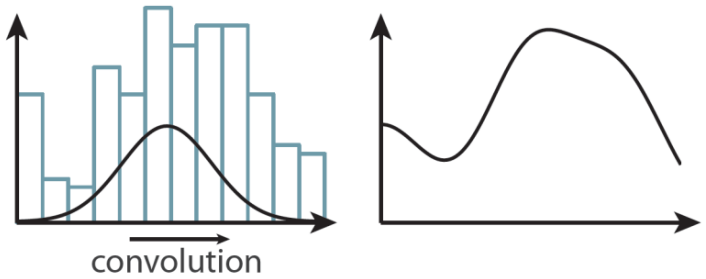
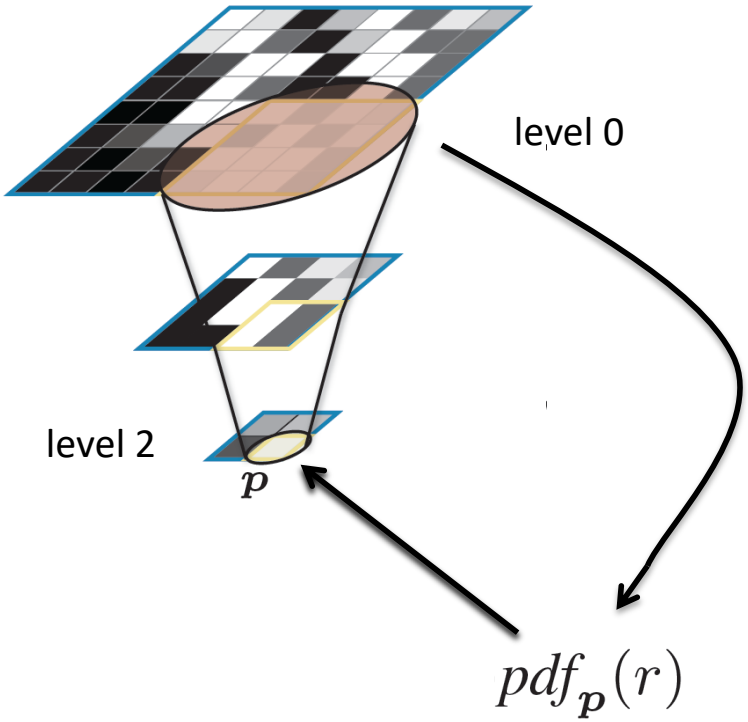


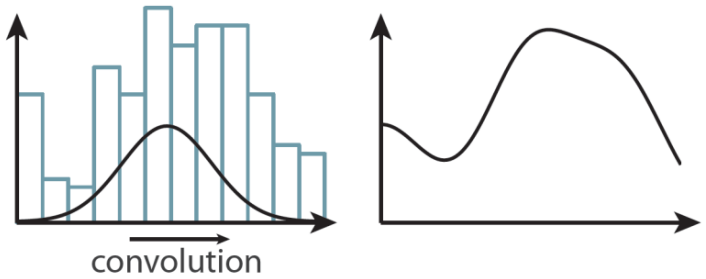


$$pdf_{\boldsymbol{p}}(r)$$

SPARSE PDF MAPS

Represent distribution of pixel values in footprint in original image





SPARSE PDF MAPS

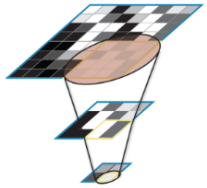
Represent distribution of pixel values in footprint in original image

Apply non-linear operation

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

EXAMPLE 1: DOWNSAMPLED IMAGE

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

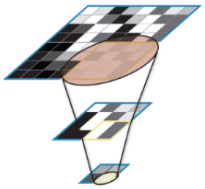


$$t_{\boldsymbol{p}}(r) = r$$

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

EXAMPLE 2: COLOR MAPPING

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

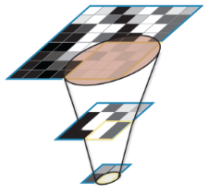


$$t_{\boldsymbol{p}}(r) = \text{color map}$$

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

EXAMPLE 2: COLOR MAPPING

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



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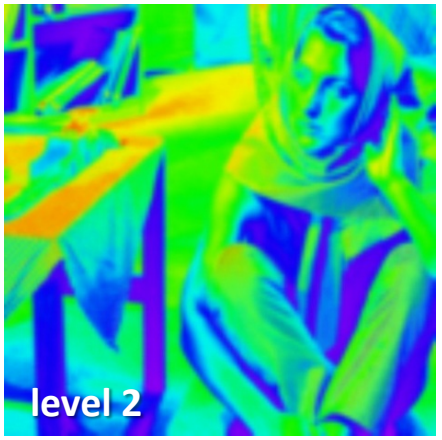
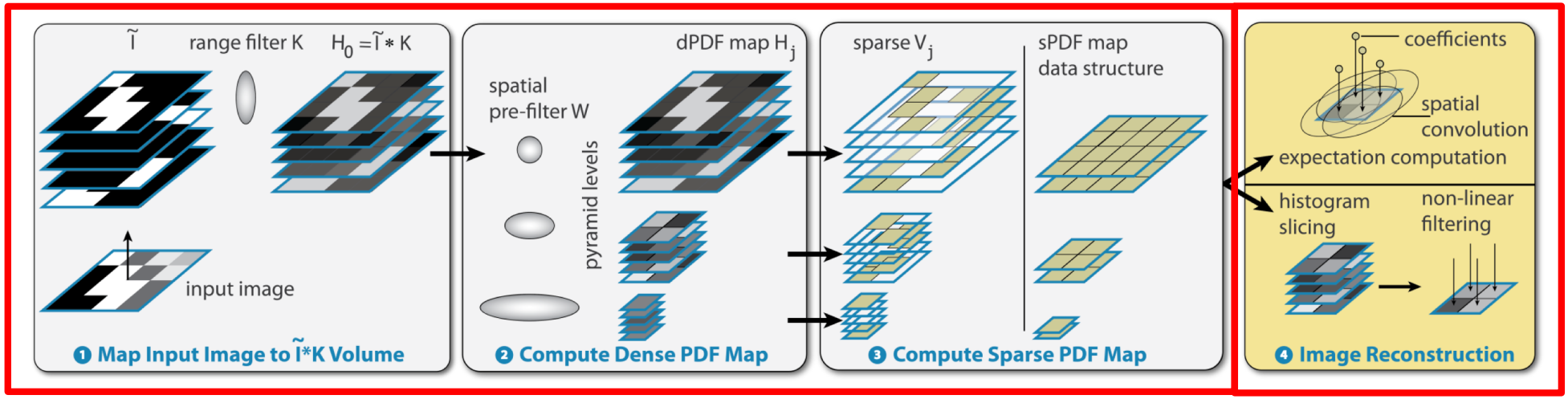


plus: bilateral filtering, local Laplacian filtering in linear time, …

INTERACTIVE GIGAPIXEL FILTERING

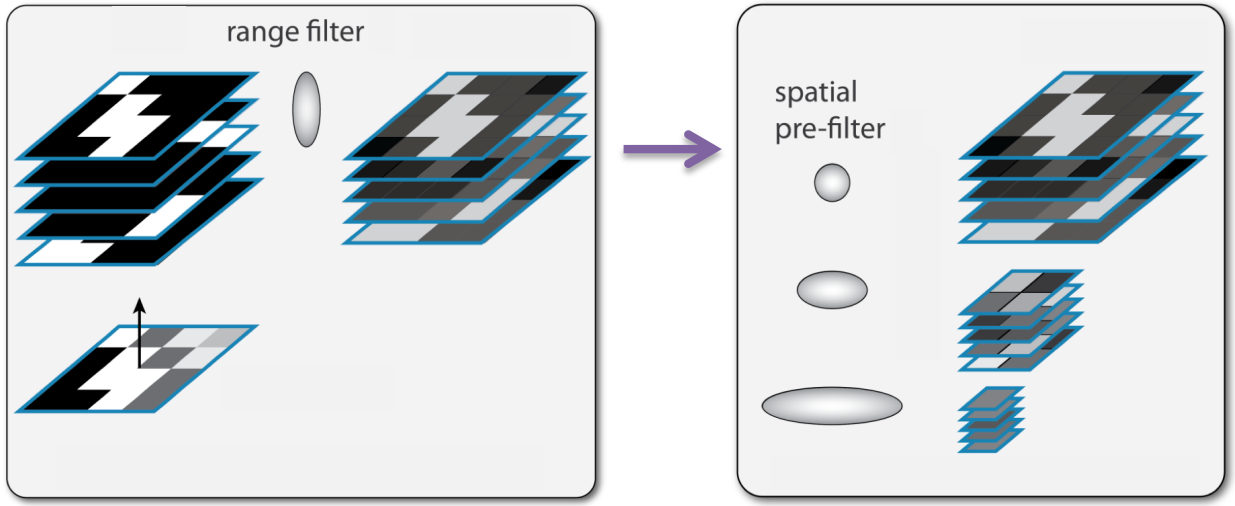
Sparse PDF Map Computation

PIPELINE


Ĩ
range filter K
$H_0 = \tilde{I} * K$
input image
1 Map Input Image to Ĩ*K Volume
dPDF map H_j
spatial
pre-filter W
pyramid levels
2 Compute Dense PDF Map
sparse V_j
sPDF map
data structure
3 Compute Sparse PDF Map
coefficients
spatial
convolution
expectation computation
histogram
slicing
non-linear
filtering
4 Image Reconstruction

STEP 1: DENSE PDF MAP

DENSE PDF MAP COMPUTATION



H is similar to a pyramid of bilateral grids [Chen et al. 2007]

STEP 2: SPARSE PDF MAP

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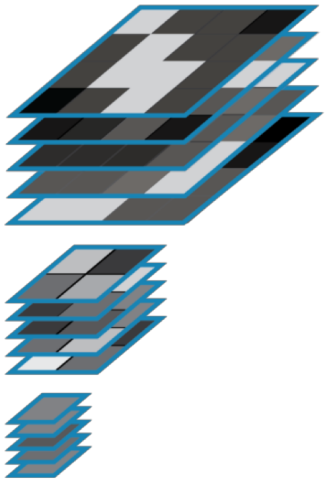
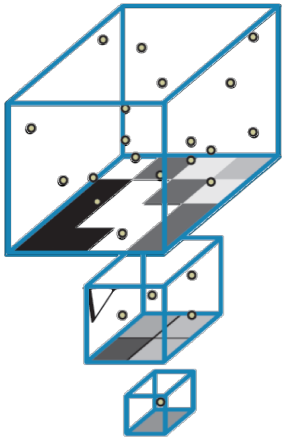
SPARSE REPRESENTATION

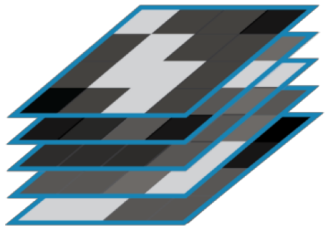


$$H \approx V * (W \otimes K)$$

$$G_{\boldsymbol{\sigma}_s} \otimes G_{\sigma_r}$$

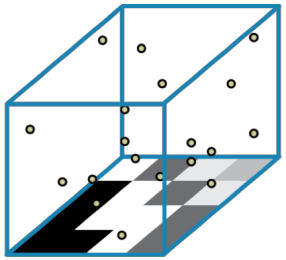


SPARSE REPRESENTATION



$$H \approx V * (W \otimes K)$$

$$G_{\boldsymbol{\sigma}_s} \otimes G_{\sigma_r}$$



Compute via Matching Pursuit [Mallat and Zhang 1993]

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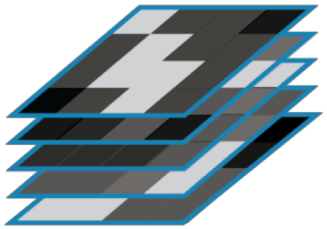
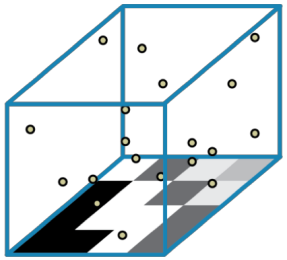
SPARSE REPRESENTATION



$$H \approx V * (W \otimes K)$$



$$V(\boldsymbol{p}_n, r_n) = c_n \qquad c_n \neq 0$$

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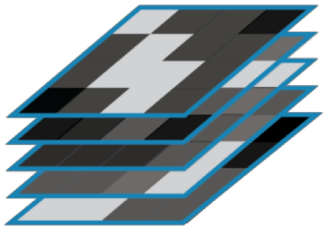
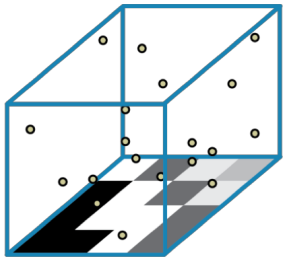
SPARSE REPRESENTATION



$$H \approx V * (W \otimes K)$$



$$V(\boldsymbol{p}_n, r_n) = c_n \qquad c_n \neq 0$$

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

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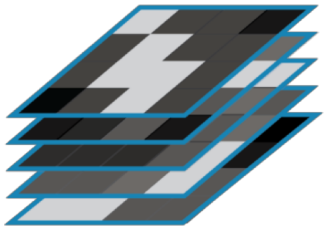
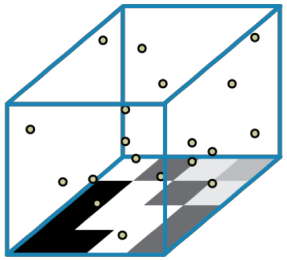
SPARSE REPRESENTATION



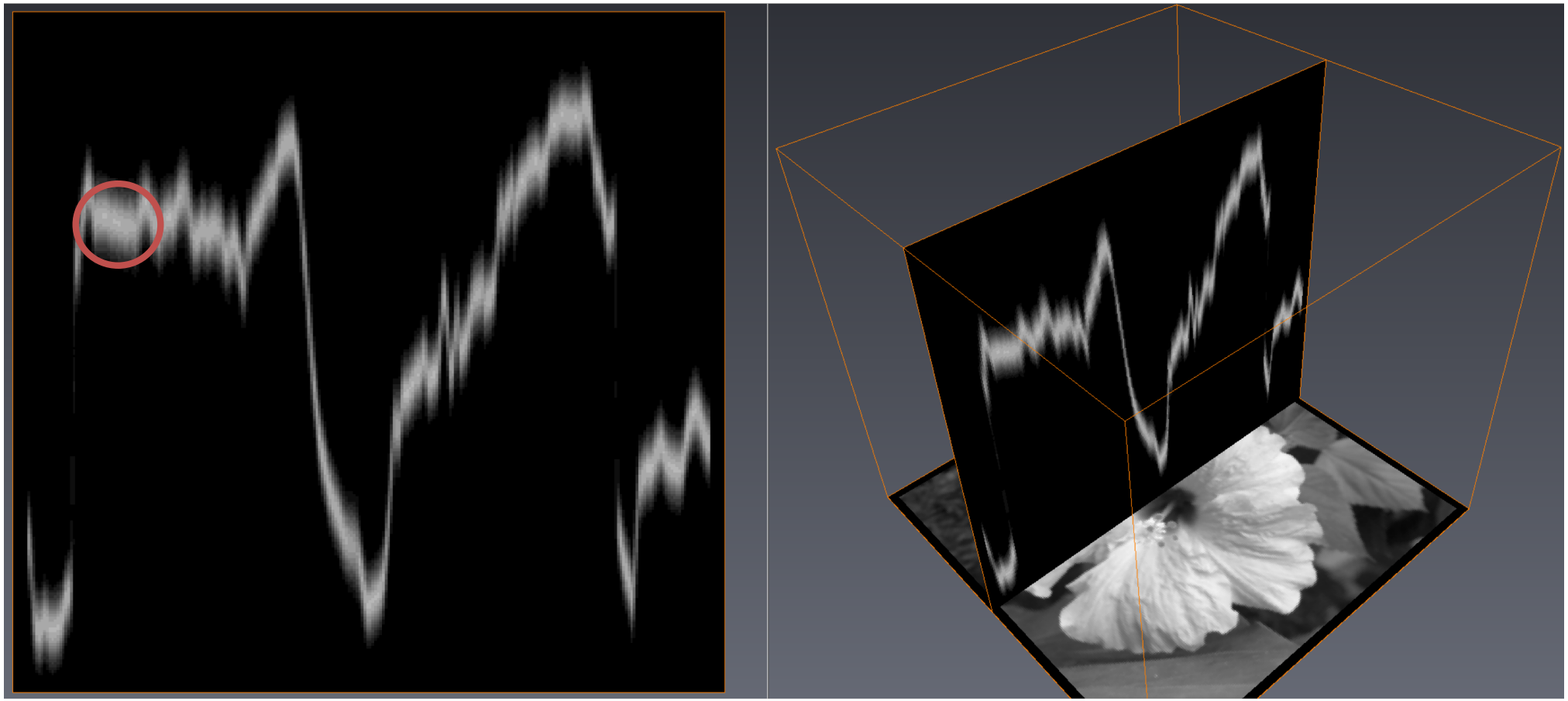
$$H \approx V * (W \otimes K)$$



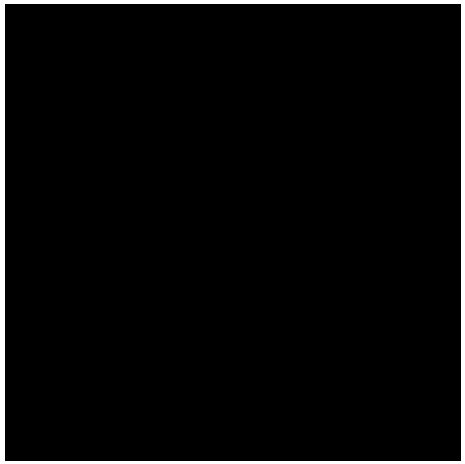
$$V(\boldsymbol{p}_n, r_n) = c_n \qquad c_n \neq 0$$

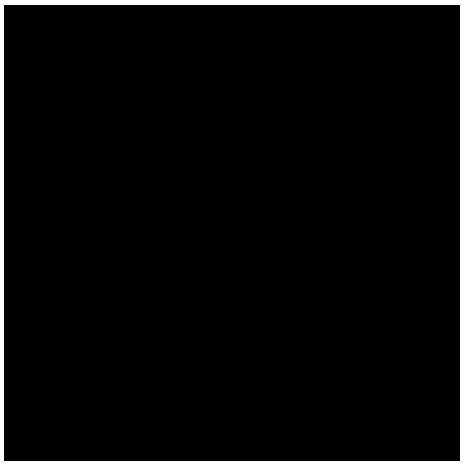
$$(\boldsymbol{p}_n, r_n, c_n)$$

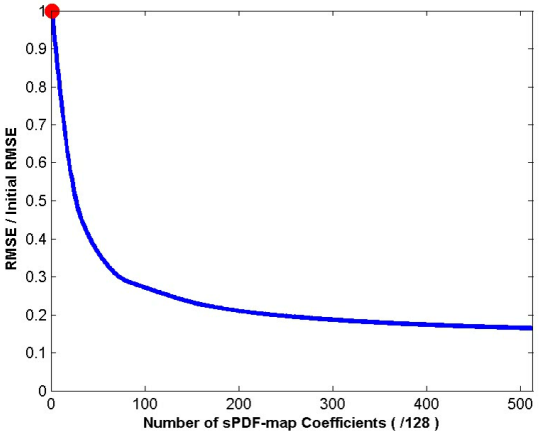
SPATIAL AND RANGE COHERENCE

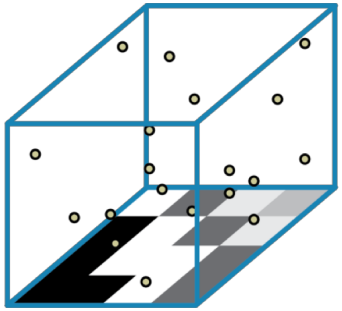


GREEDY APPROXIMATION







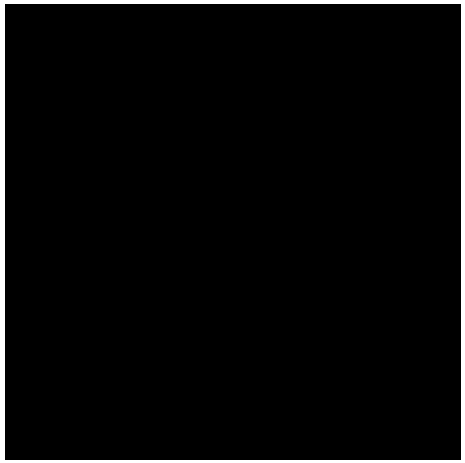


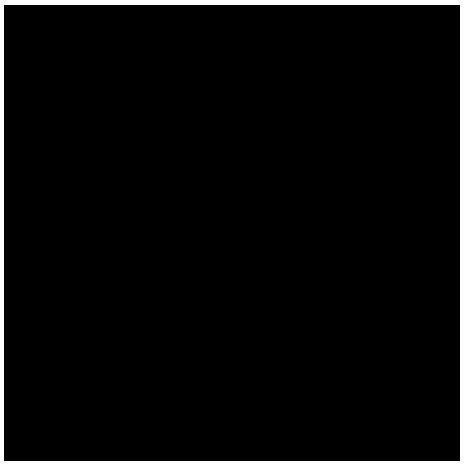
Spatial filter W : 5 x 5

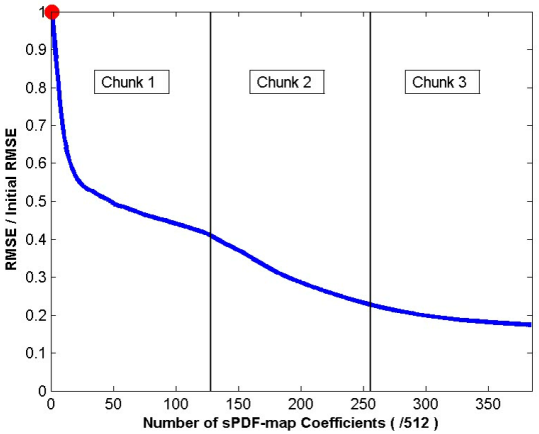
1 coefficient chunk

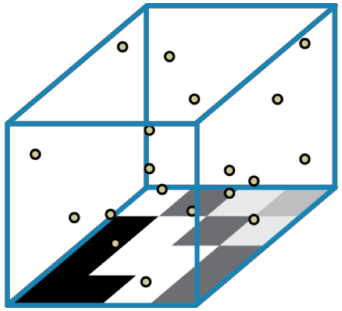
(# coefficients == 1 * # pixels)

GREEDY APPROXIMATION









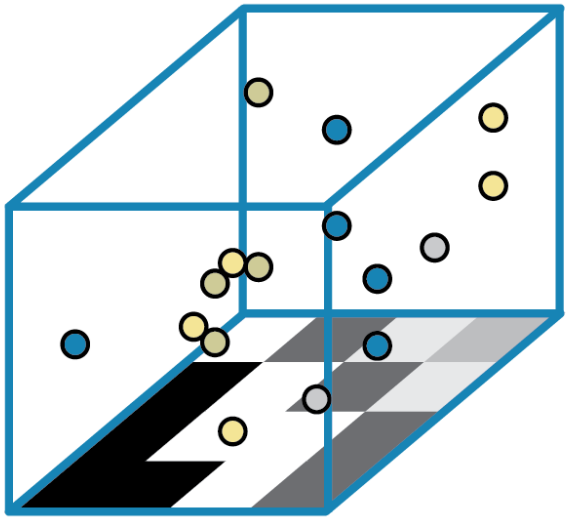
Spatial filter W : 3 x 3

1-3 coefficient chunks

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

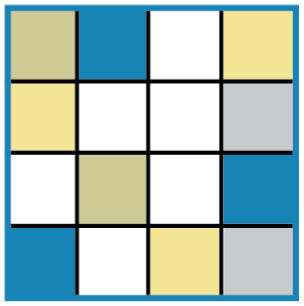
sPDF-Maps Data Structure

SPDF-MAPS DATA STRUCTURE



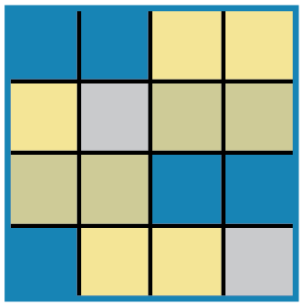
conceptual

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



index image

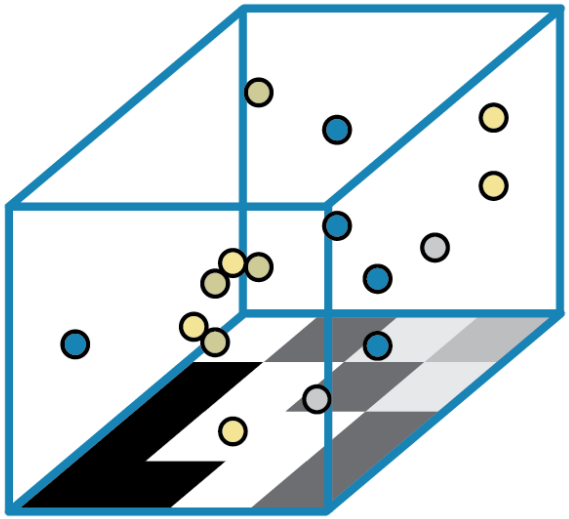
$$(index, count)_{\boldsymbol{p}}$$



coefficient image

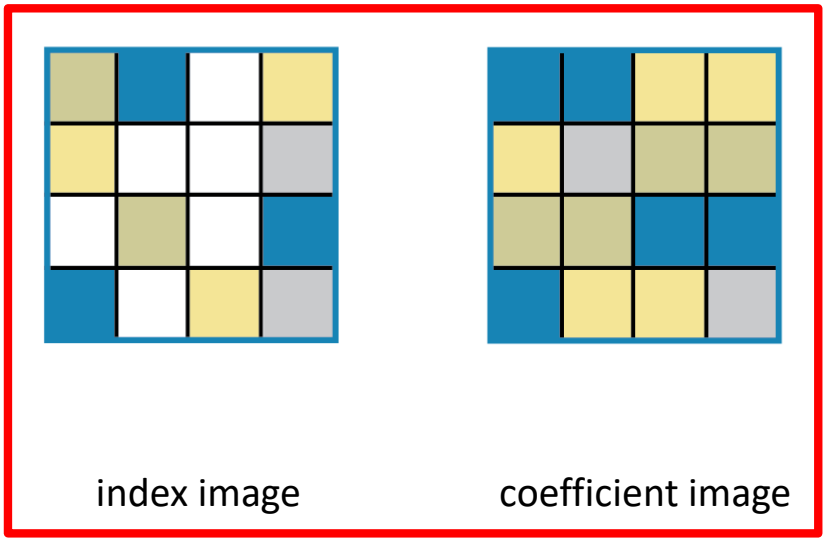
$$(r_n, c_n)$$

SPDF-MAPS DATA STRUCTURE



conceptual

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



index image

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

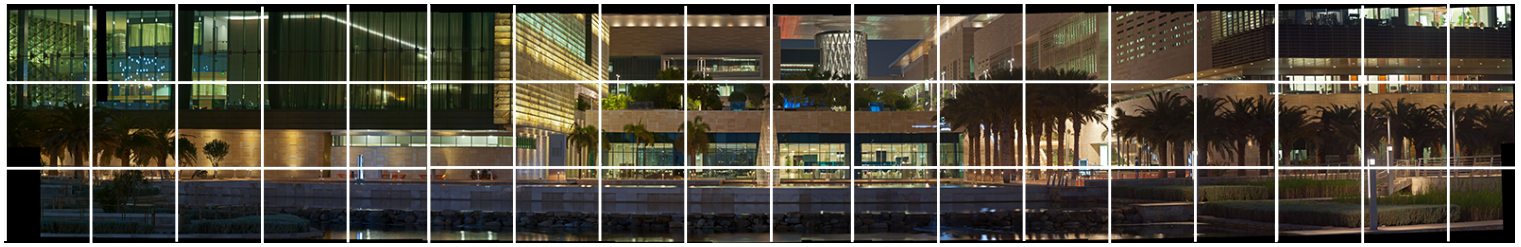
coefficient image

$$(r_n, c_n)$$

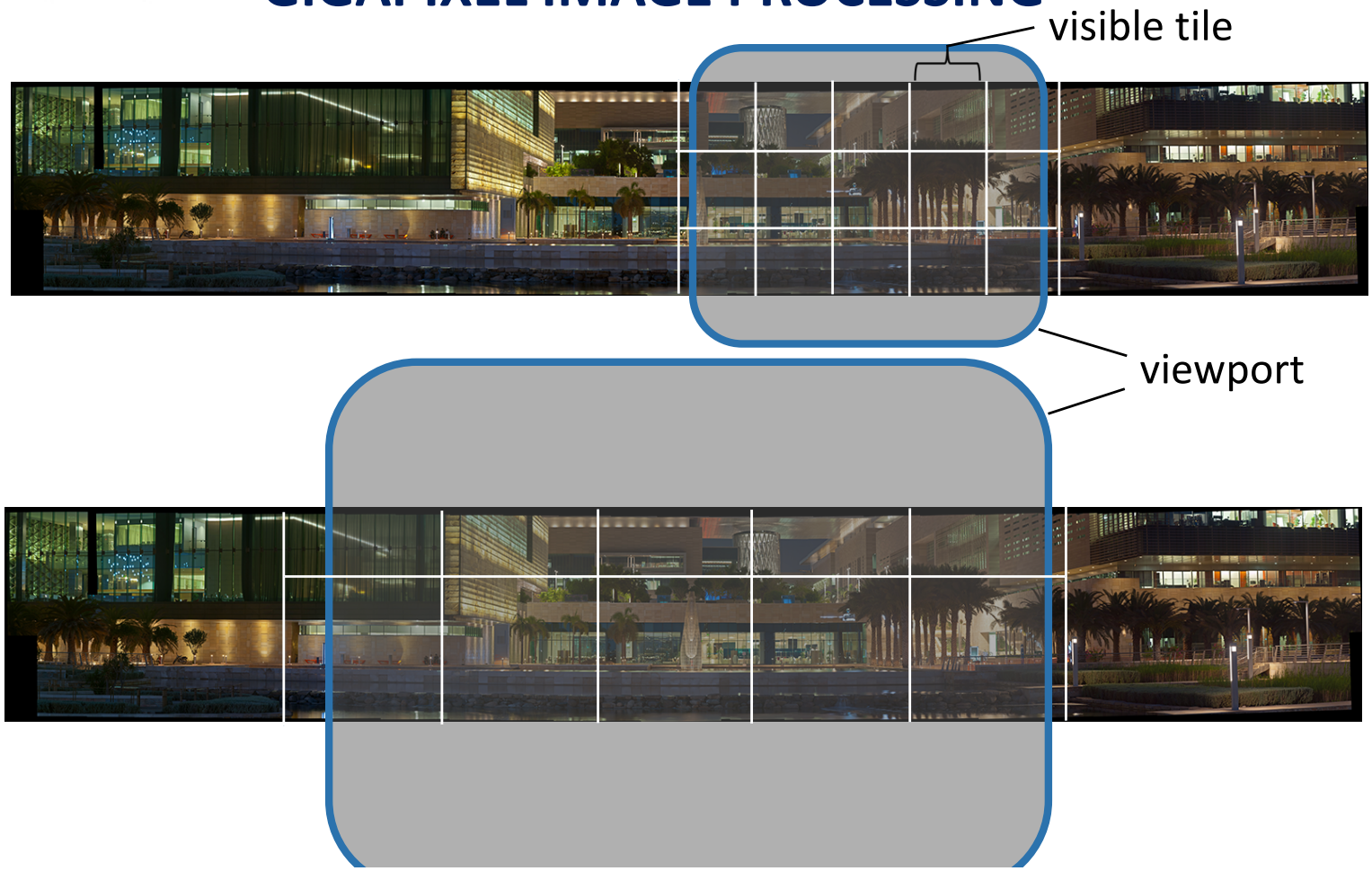
Display-Aware Gigapixel Image Processing

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]

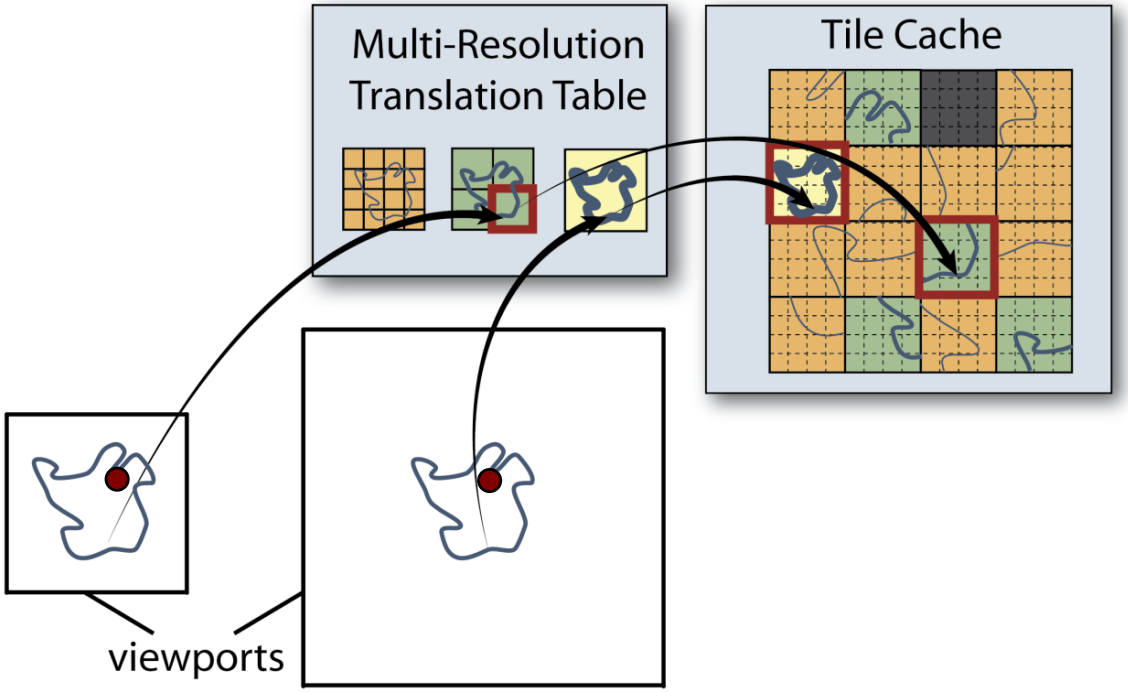
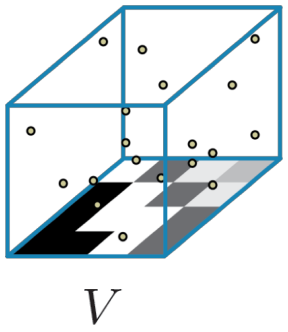


Image Reconstruction

IMAGE RECONSTRUCTION

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



- Key idea # 1

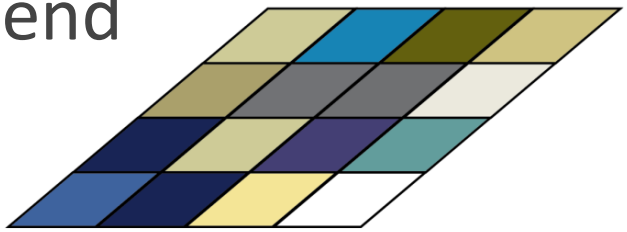
  Use $t_{\boldsymbol{p}}(r)$ instead of $pdf_{\boldsymbol{p}}(r)$

- Key idea # 2

  Pre-convolve V with K: $\tilde{t}_{\boldsymbol{p}} = t_{\boldsymbol{p}} * K$

COLOR MAPPING

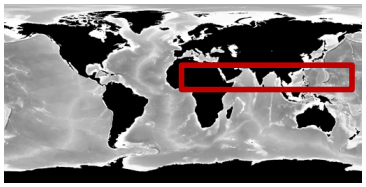
- Pre-convolve color map (with range kernel)
- For each pixel go over its coefficients
  - Apply color map to coefficient and sum up (not spatially convolved yet!)
- One spatial convolution in the end

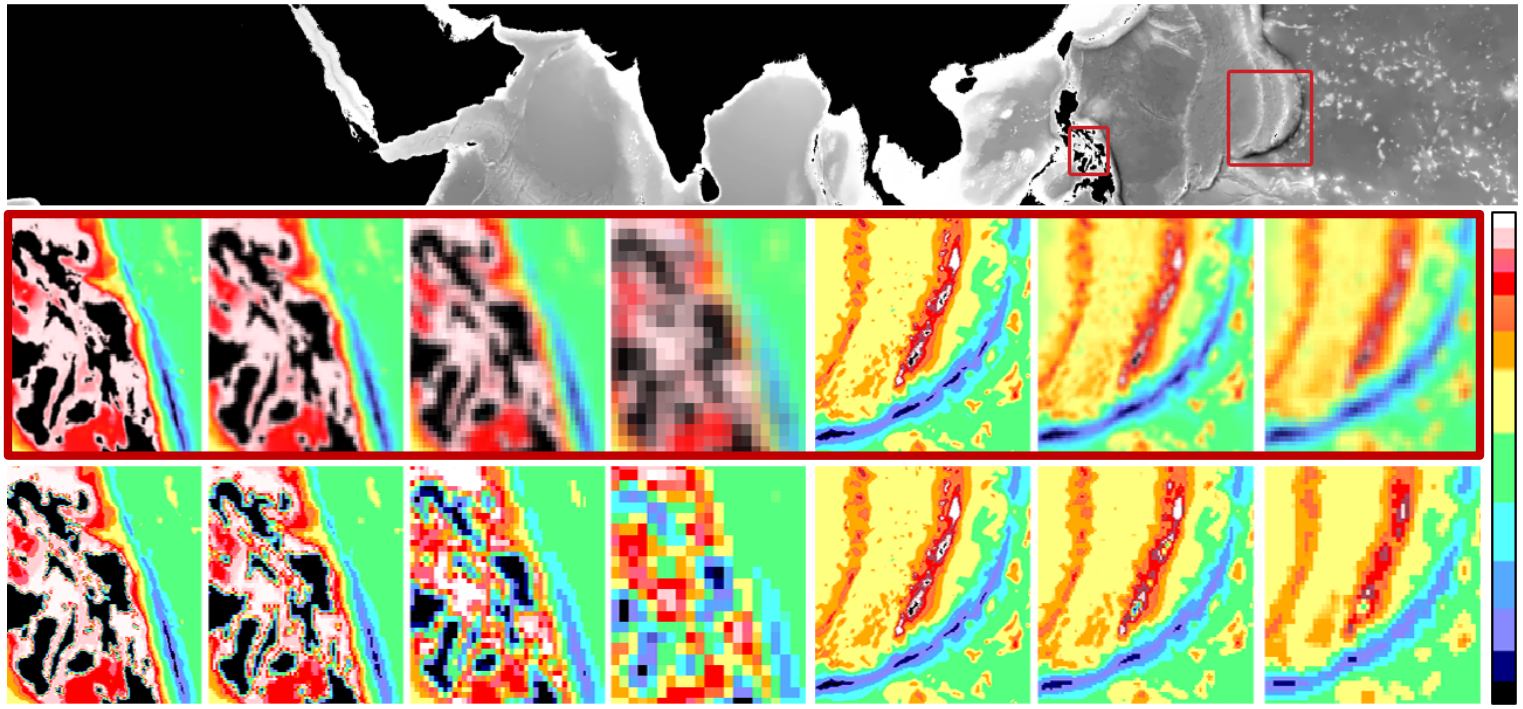


Results

COLOR MAPPING GIGAPIXEL IMAGES

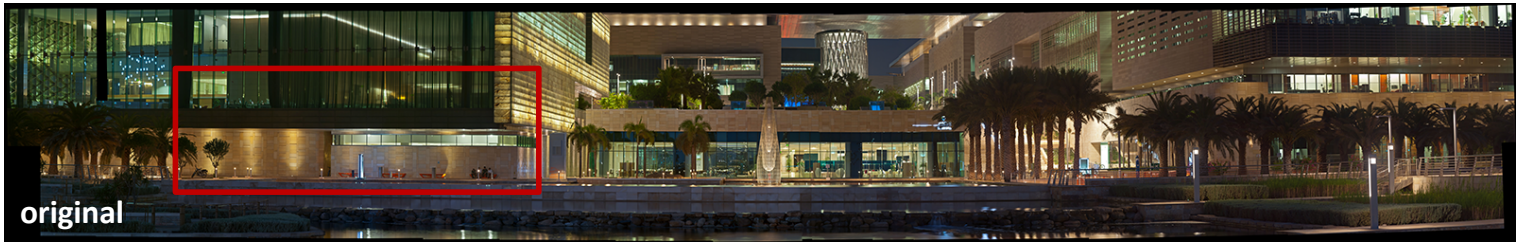
NASA Blue Marble bathymetry: 21,601 x 10,801 pixels (233 Mpixels)

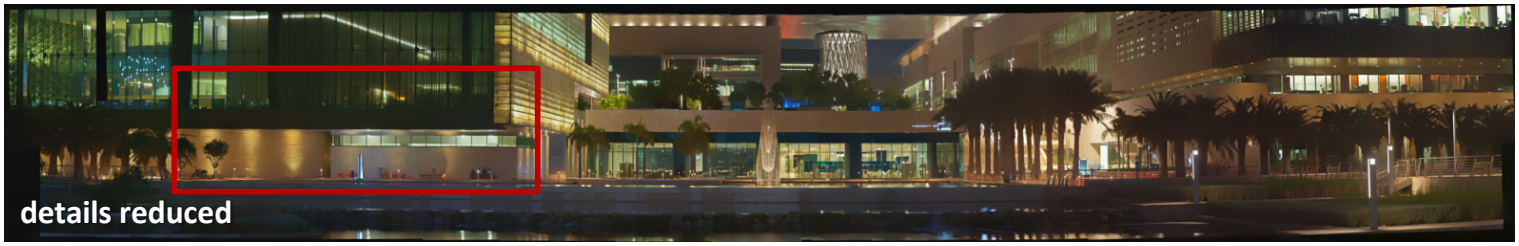


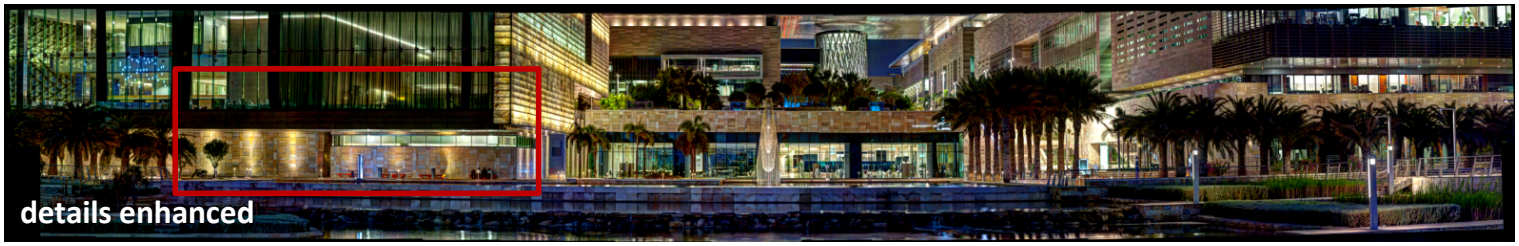



details enhanced
original
details reduced
details enhanced
original
details reduced

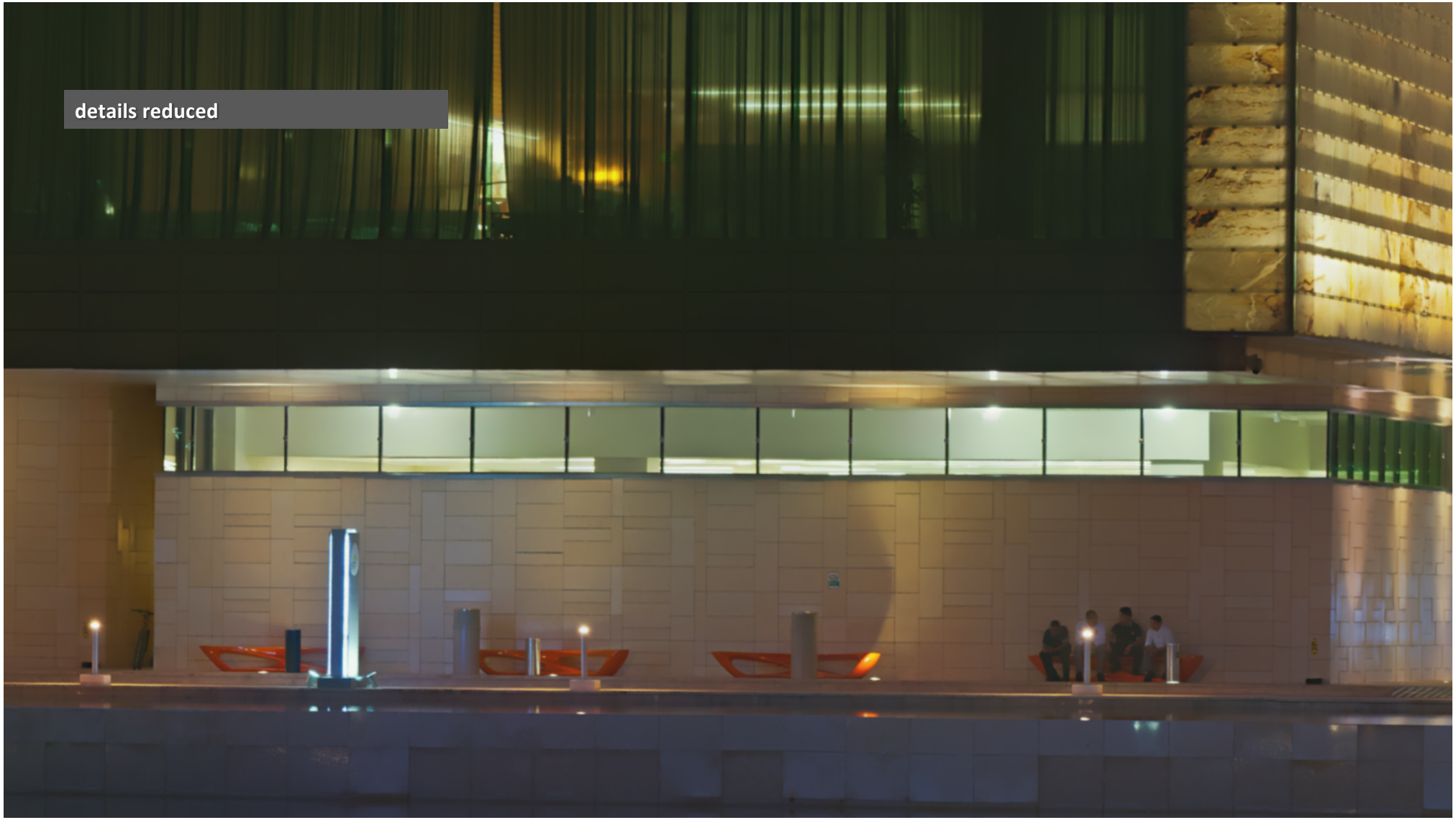
GIGAPIXEL LOCAL LAPLACIAN FILTERING

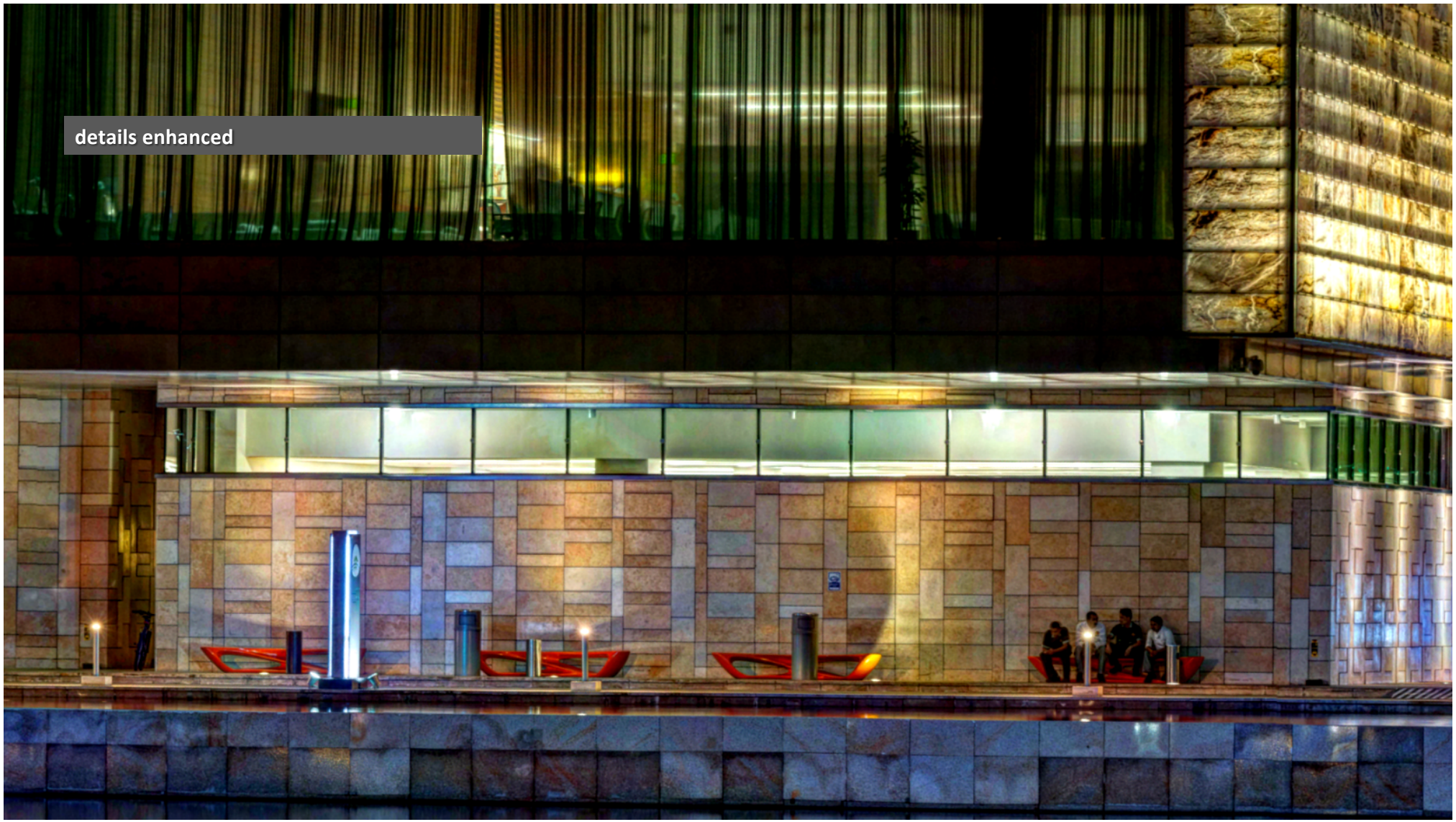







original


details reduced


details enhanced

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

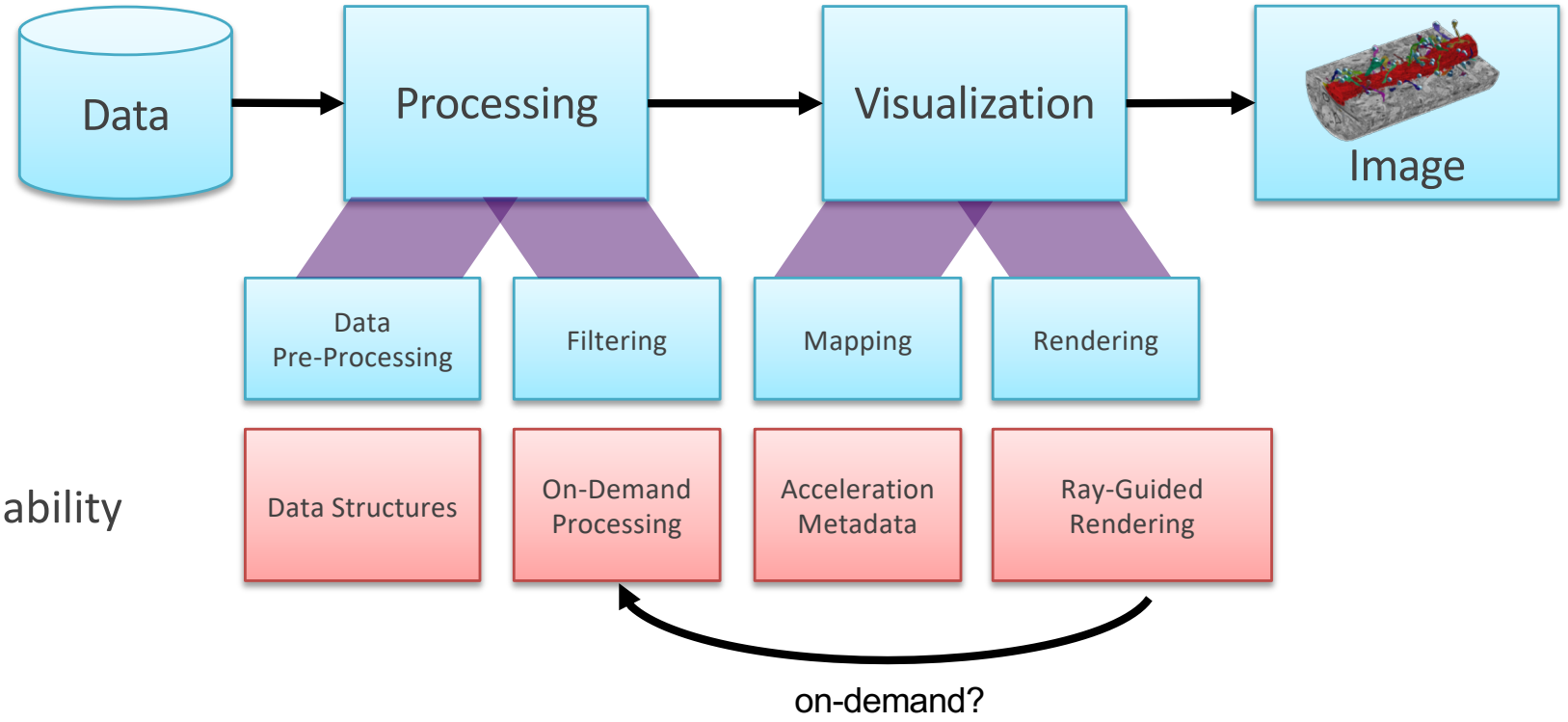
Pre-computation costly, but only performed once

Run time storage and computation similar to standard pyramids

Hadwiger, Sicat, Beyer, Krüger, Möller,
Sparse PDF Maps for Non-Linear Multi-Resolution Image Operations,
Siggraph Asia 2012

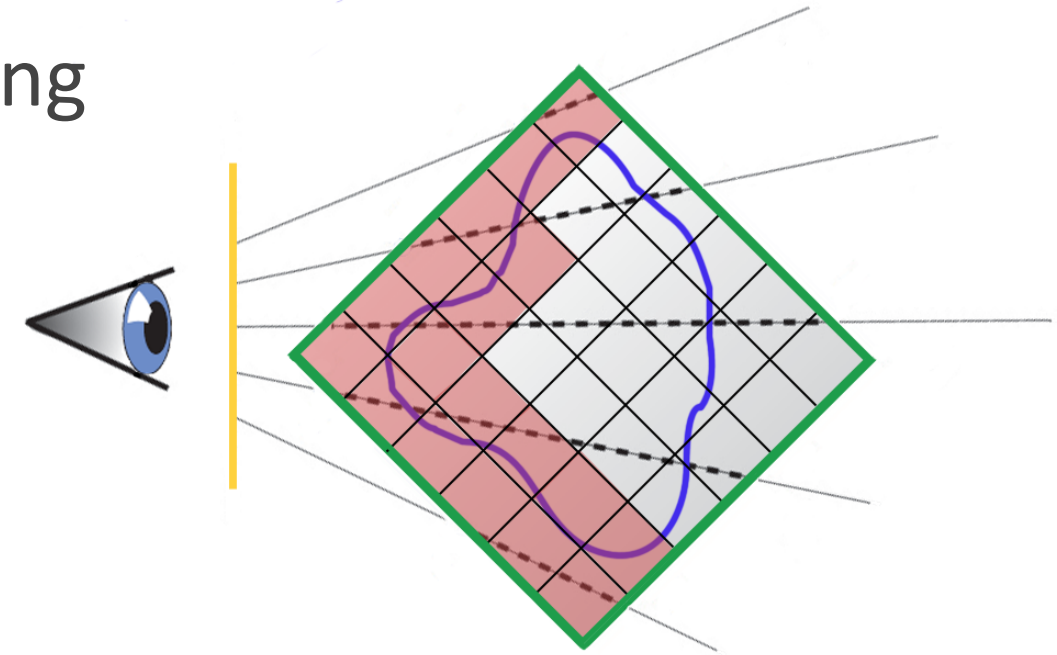
Summary & Outlook

LARGE-SCALE VISUALIZATION PIPELINE



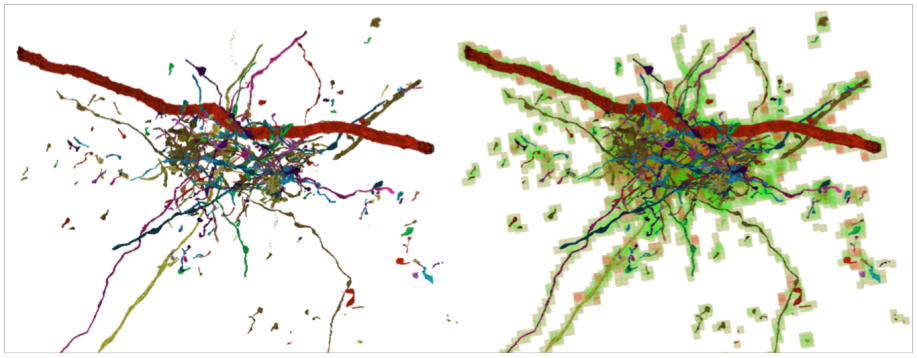
RAY-GUIDED VOLUME RENDERING

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



VOLUME RENDERING FOR 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



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