



CONFERENCE 4 – 7 December 2018  
EXHIBITION 5 – 7 December 2018  
Tokyo International Forum, Japan  
[SA2018.SIGGRAPH.ORG](http://SA2018.SIGGRAPH.ORG)

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# GPU-Based Large-Scale Scientific Visualization

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Course Website:

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





# Part 4 -

# Display-Aware Visualization and

# Processing

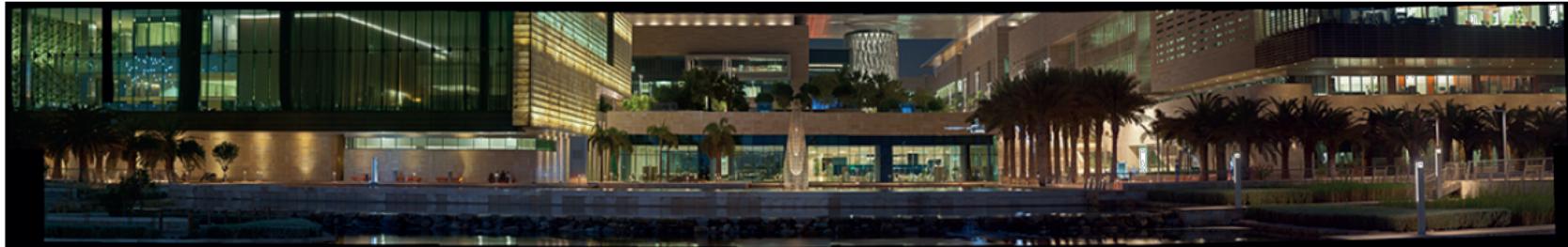


## MOTIVATION





## DISPLAY-AWARE IMAGE OPERATIONS



Input Resolution  
(level 0)

⋮



Output Resolution  
(level 3)

Display Region



Compute Resolution  
(level 4)

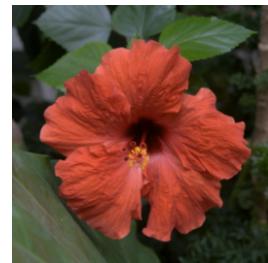
Compute Region

## 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



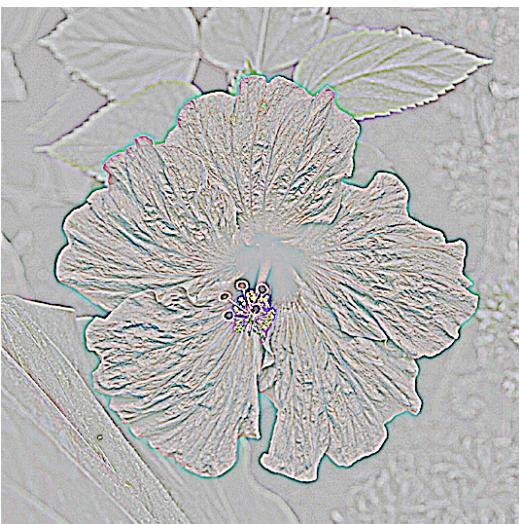
level 2



level 3

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level 0



level 1



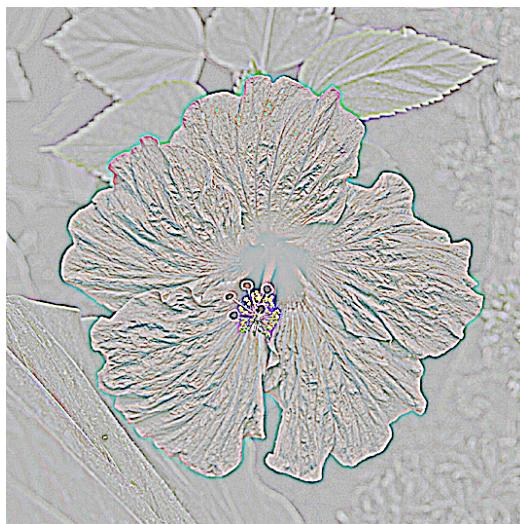
level 2



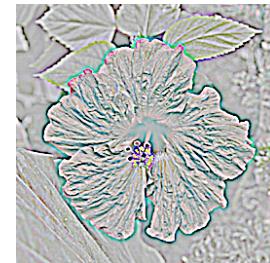
level 3

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level 0



level 1



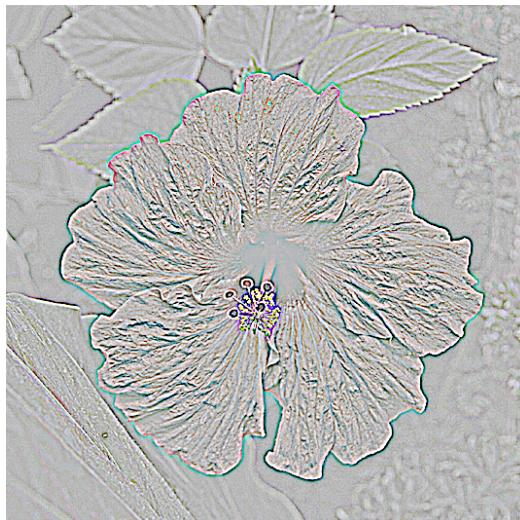
level 2



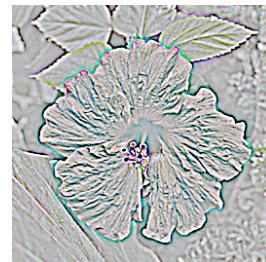
level 3

## 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

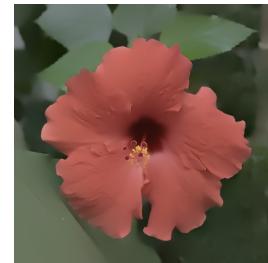
Laplacian pyramid

## 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



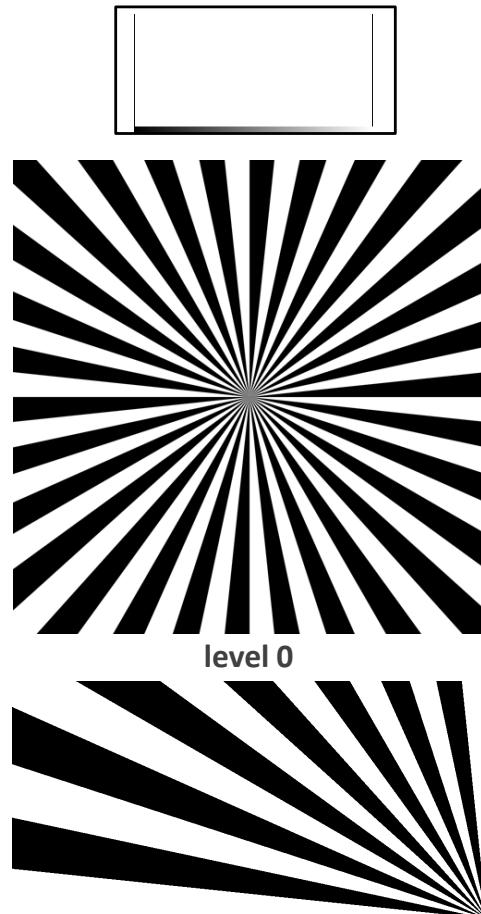
level 2



level 3

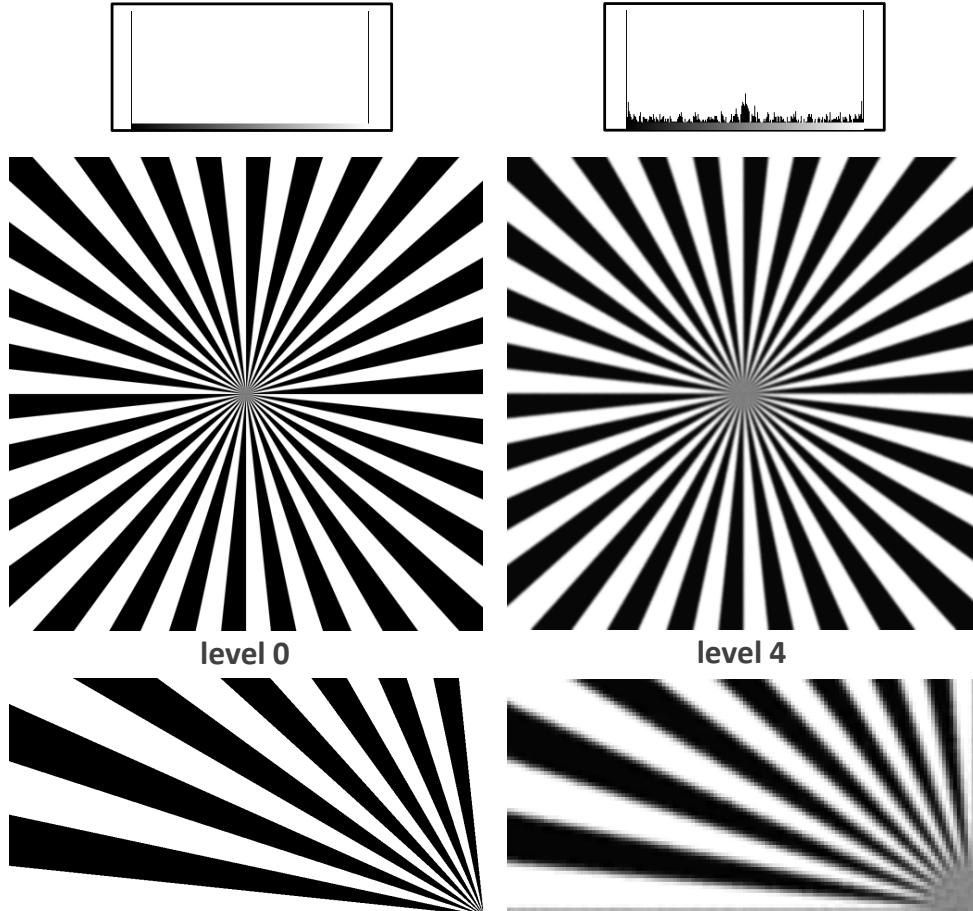


## ANTI-ALIASING IN IMAGE PYRAMIDS



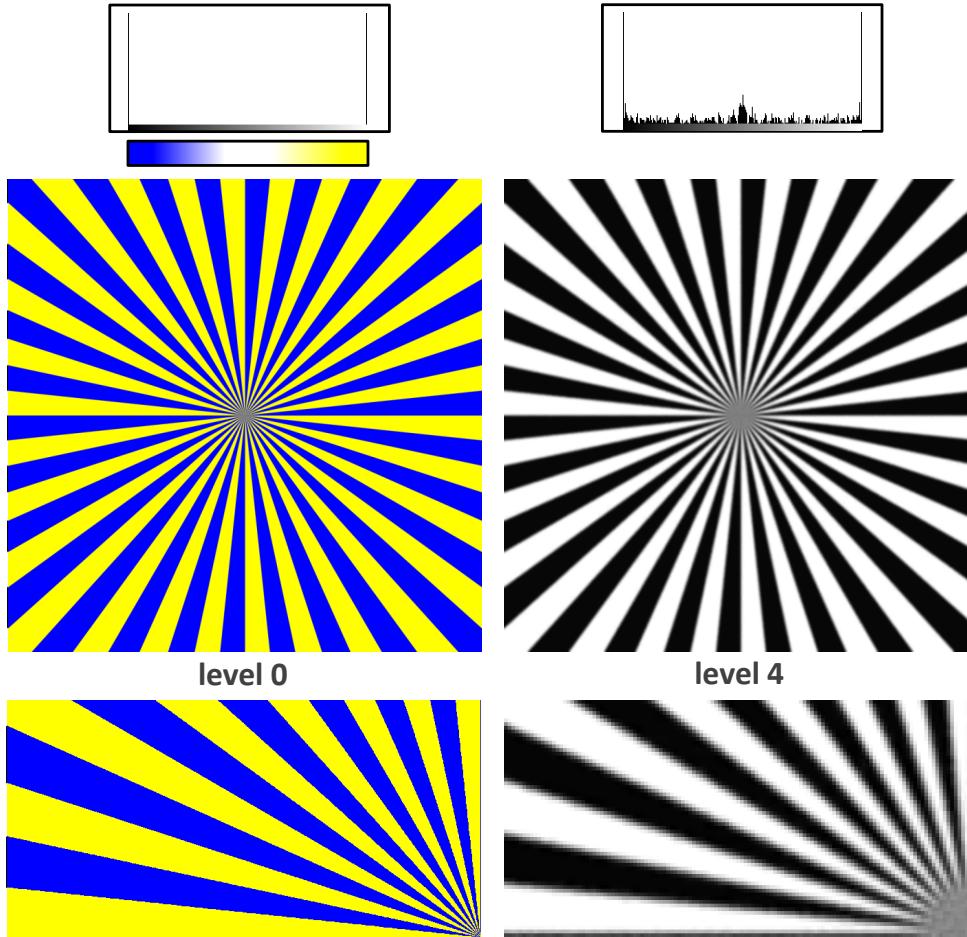


## ANTI-ALIASING IN IMAGE PYRAMIDS



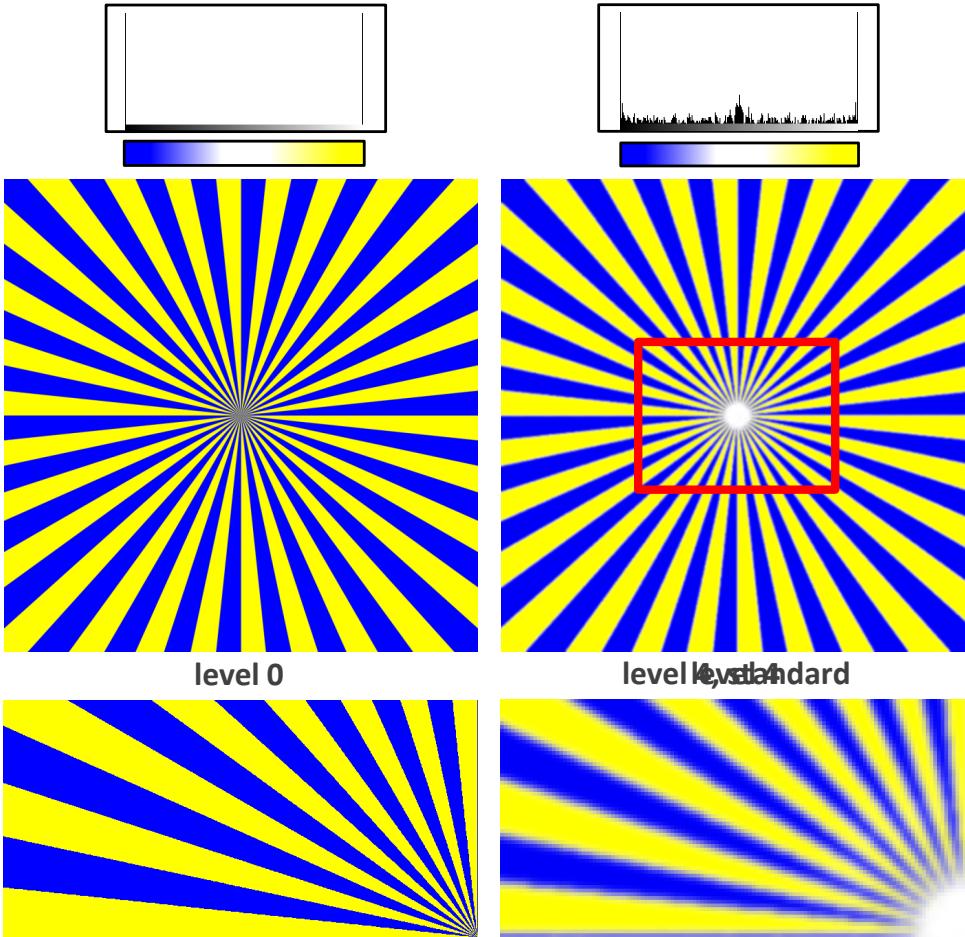


## ANTI-ALIASING IN IMAGE PYRAMIDS



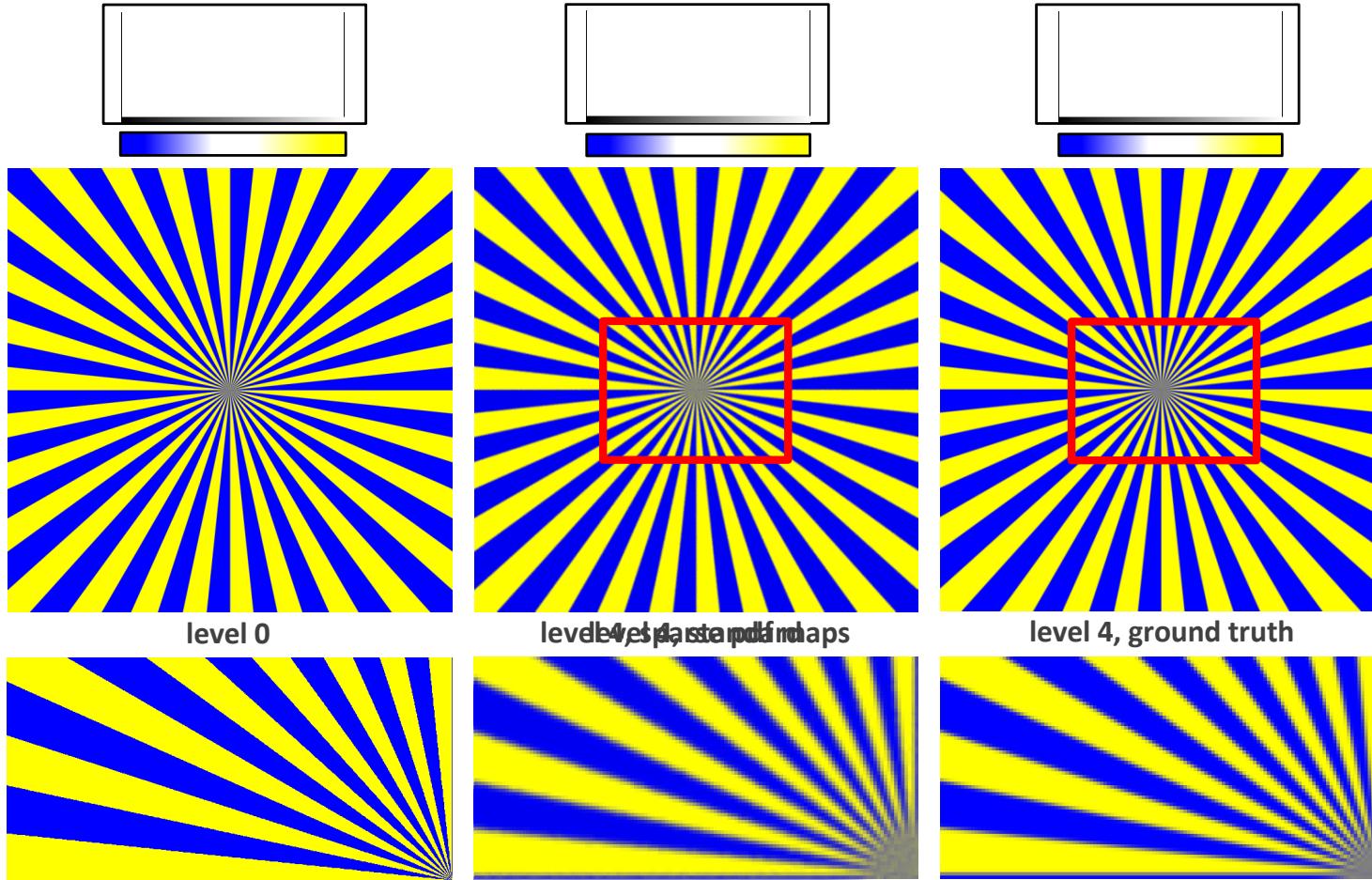


## ANTI-ALIASING IN IMAGE PYRAMIDS





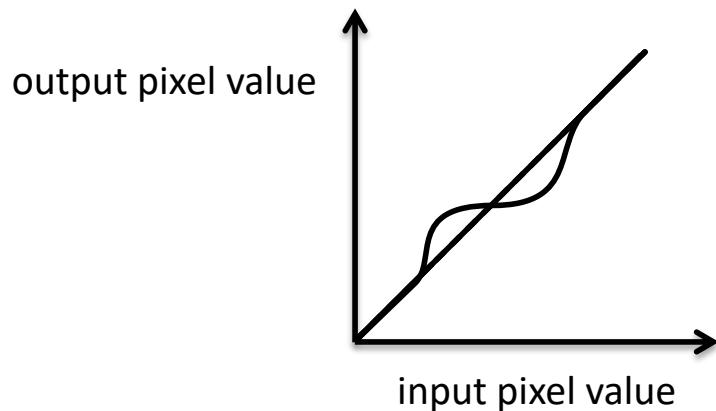
## ANTI-ALIASING IN IMAGE PYRAMIDS



## NON-LINEAR IMAGE OPERATORS

Apply non-linear operation to each pixel

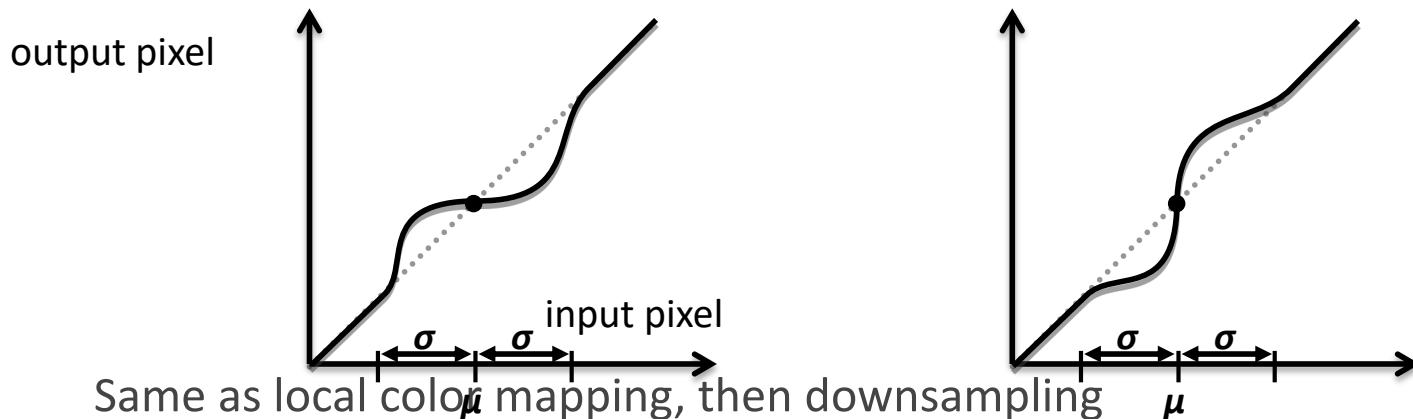
- Color map or non-linear contrast adjustment
- Bilateral filtering: range weight
- Smoothed local histogram filtering [Kass and Solomon 2010]
- Local Laplacian filtering [Paris et al. 2011]: point-wise, non-linear re-mapping



## LOCAL LAPLACIAN FILTERING [PARIS ET AL. 2011]

Compute Laplacian pyramid coefficient

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

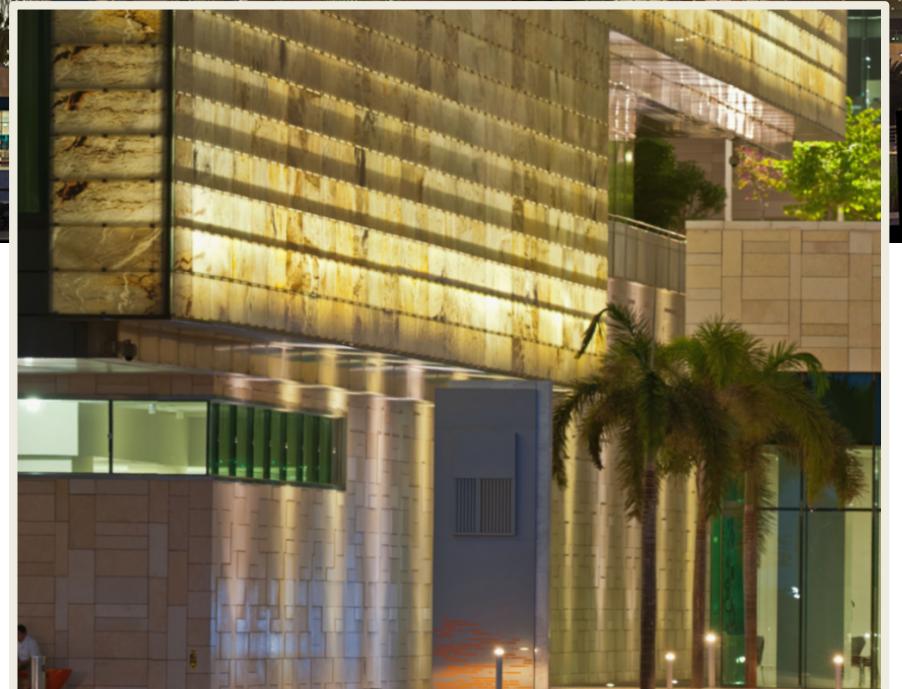
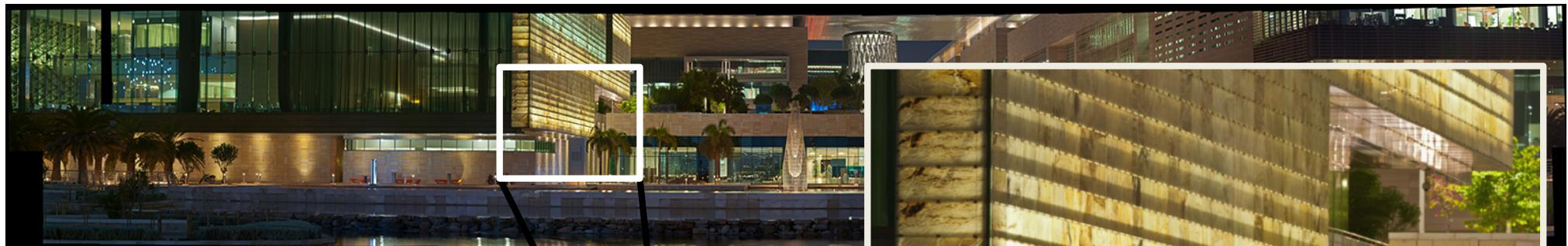


- Cannot apply the re-mapping function to the downsampled image!
- Need to compute ground truth (pyramid!) or proper “anti-aliasing”



## 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!

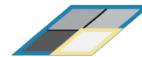
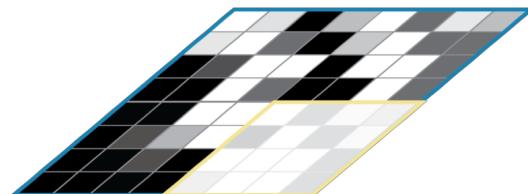


# Sparse PDF Maps: Concept



## SPARSE PDF MAPS

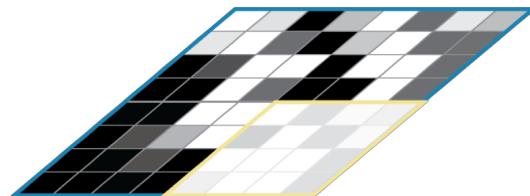
Represent distribution of pixel values in footprint in original image





## SPARSE PDF MAPS

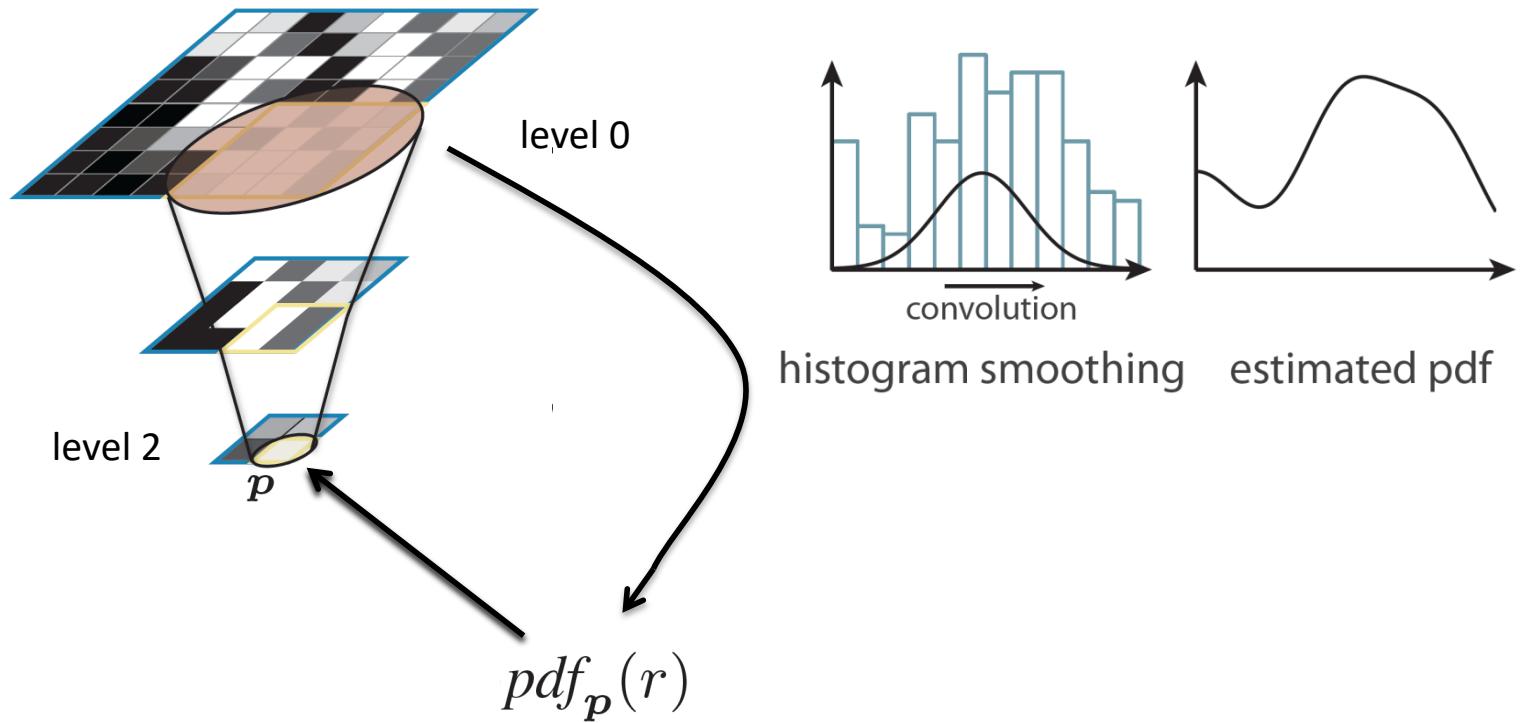
Represent distribution of pixel values in footprint in original image



level 2       $p$  A small version of the sparse PDF map shown above, with a yellow oval highlighting a single point labeled  $p$ .

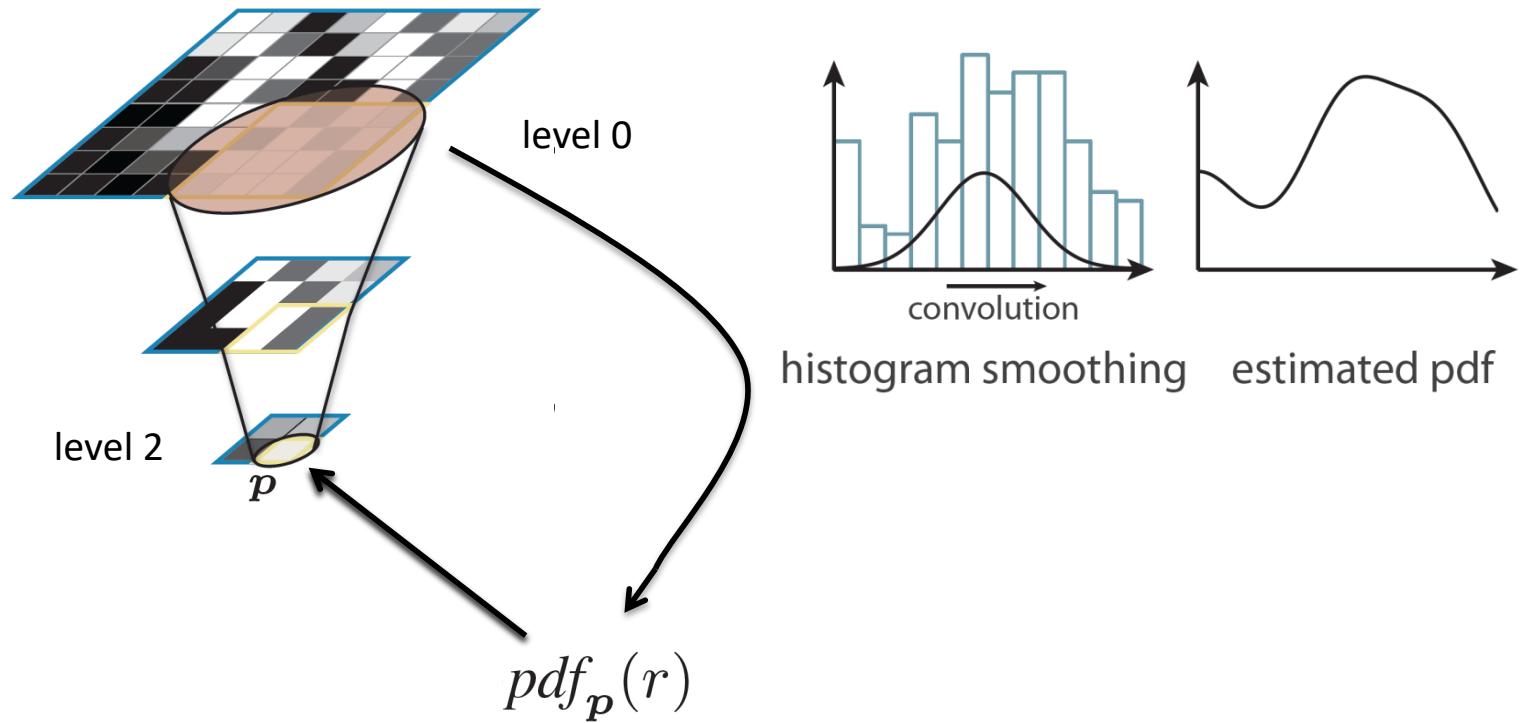
## SPARSE PDF MAPS

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

Apply non-linear operation

The diagram illustrates a sparse PDF map at level 2. A small yellow oval represents a footprint on a blue surface patch labeled 'p'. An arrow points from this footprint to a mathematical expression below. The expression is:

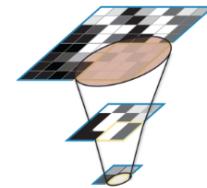
$$E[t_p(X_p)] = \frac{1}{w_p} \int_0^1 t_p(r) pdf_p(r) dr$$

The terms  $t_p(r)$  and  $pdf_p(r)$  are highlighted with red boxes.



## EXAMPLE 1: DOWNSAMPLED IMAGE

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



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

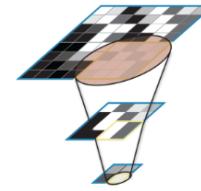
$$w_{\mathbf{p}} = 1$$





## EXAMPLE 2: COLOR MAPPING

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



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

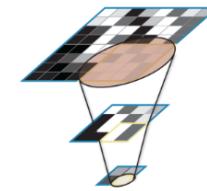
$w_{\mathbf{p}} = 1$





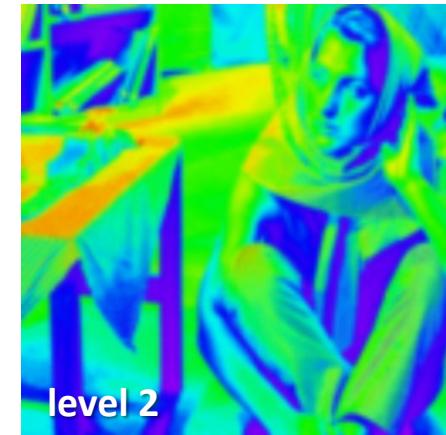
## EXAMPLE 2: COLOR MAPPING

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



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

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



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



## INTERACTIVE GIGAPIXEL FILTERING



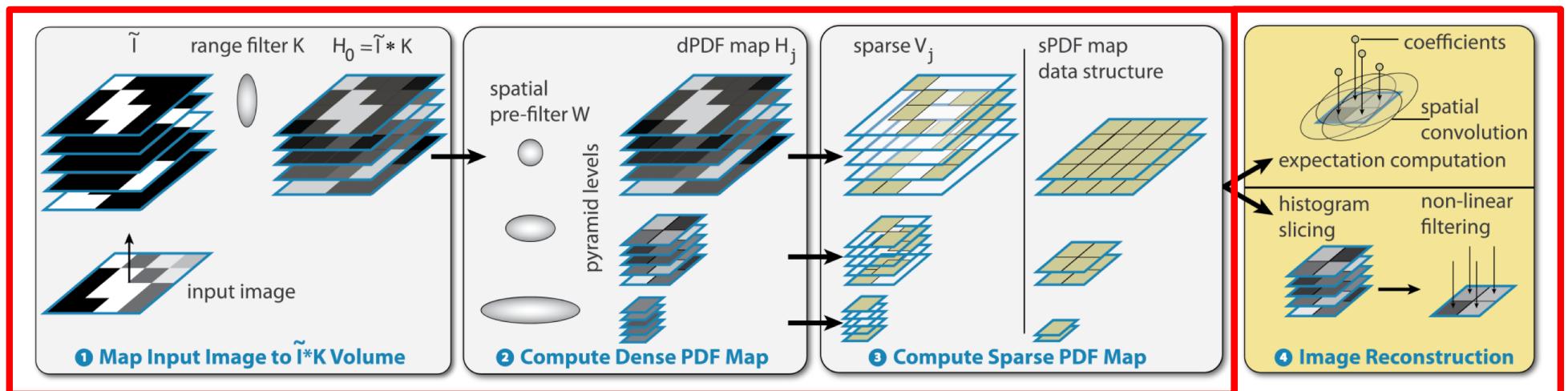
Fast Local Laplacian Filtering



# Sparse PDF Map Computation



# PIPELINE

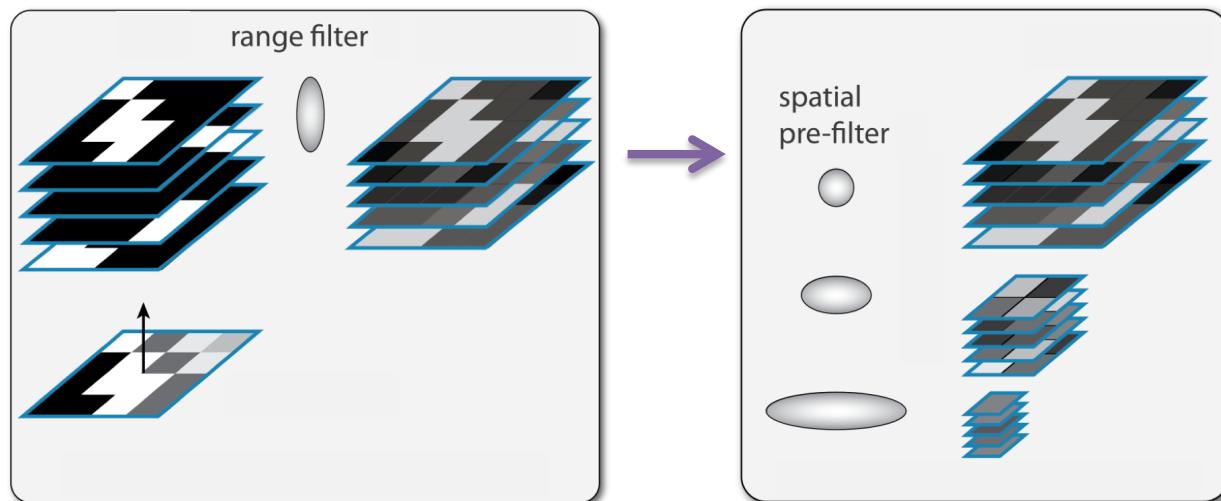




## STEP 1: DENSE PDF MAP



## DENSE PDF MAP COMPUTATION



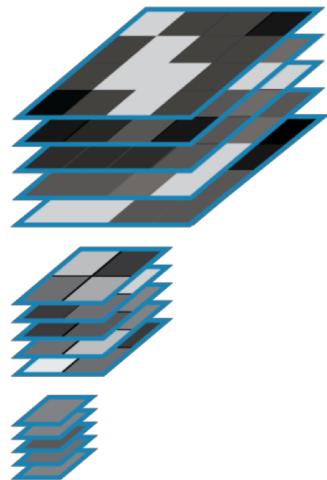
$H$  is similar to a pyramid of bilateral grids [Chen et al. 2007]



## STEP 2: SPARSE PDF MAP



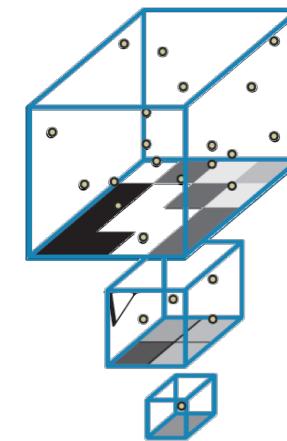
## SPARSE REPRESENTATION



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

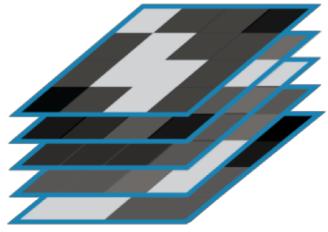
$G_{\sigma_s} \otimes G_{\sigma_r}$

A diagram showing the sparse representation of a feature map  $H$ . It is approximated as the convolution  $V$  of a sparse kernel  $(W \otimes K)$ . The kernel is generated by the tensor product of two sparse filters  $G_{\sigma_s}$  and  $G_{\sigma_r}$ .

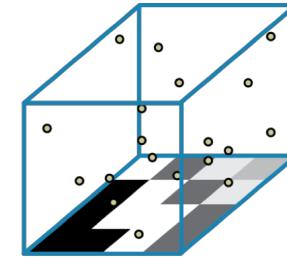




## SPARSE REPRESENTATION



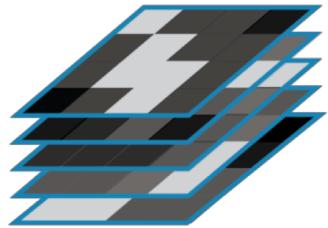
$$H \approx V * (W \otimes K)$$
$$\begin{matrix} \uparrow \\ G_{\sigma_s} \otimes G_{\sigma_r} \end{matrix}$$



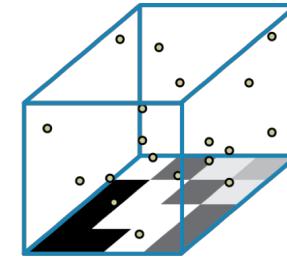
Compute via Matching Pursuit [Mallat and Zhang 1993]



## SPARSE REPRESENTATION



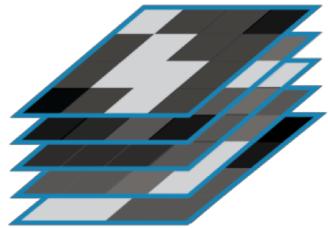
$$H \approx V * (W \otimes K)$$



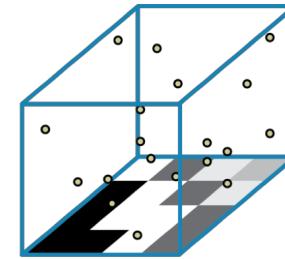
$$V(p_n, r_n) = c_n \quad c_n \neq 0$$



## SPARSE REPRESENTATION



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

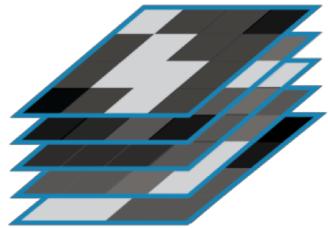


$$V(\mathbf{p}_n, r_n) = c_n \quad c_n \neq 0$$

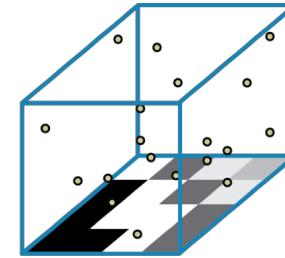
$$(\mathbf{p}_n, r_n, c_n)$$



## SPARSE REPRESENTATION



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

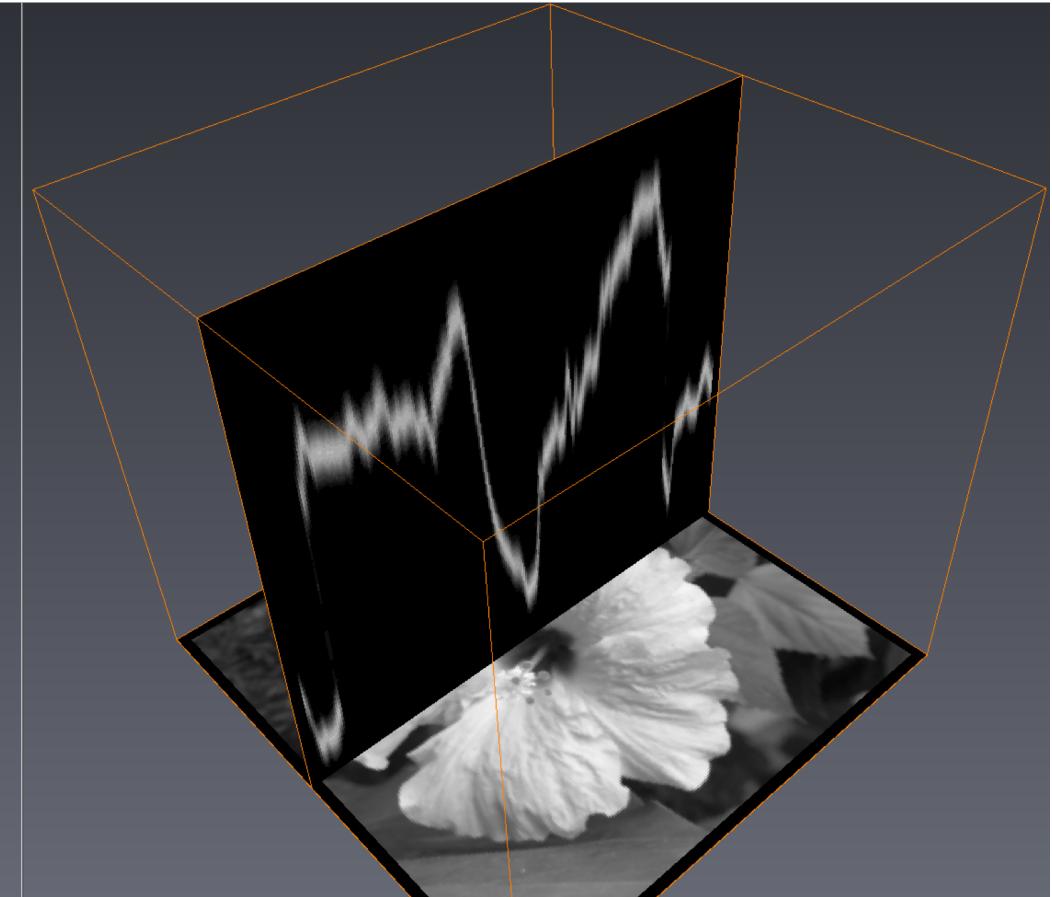
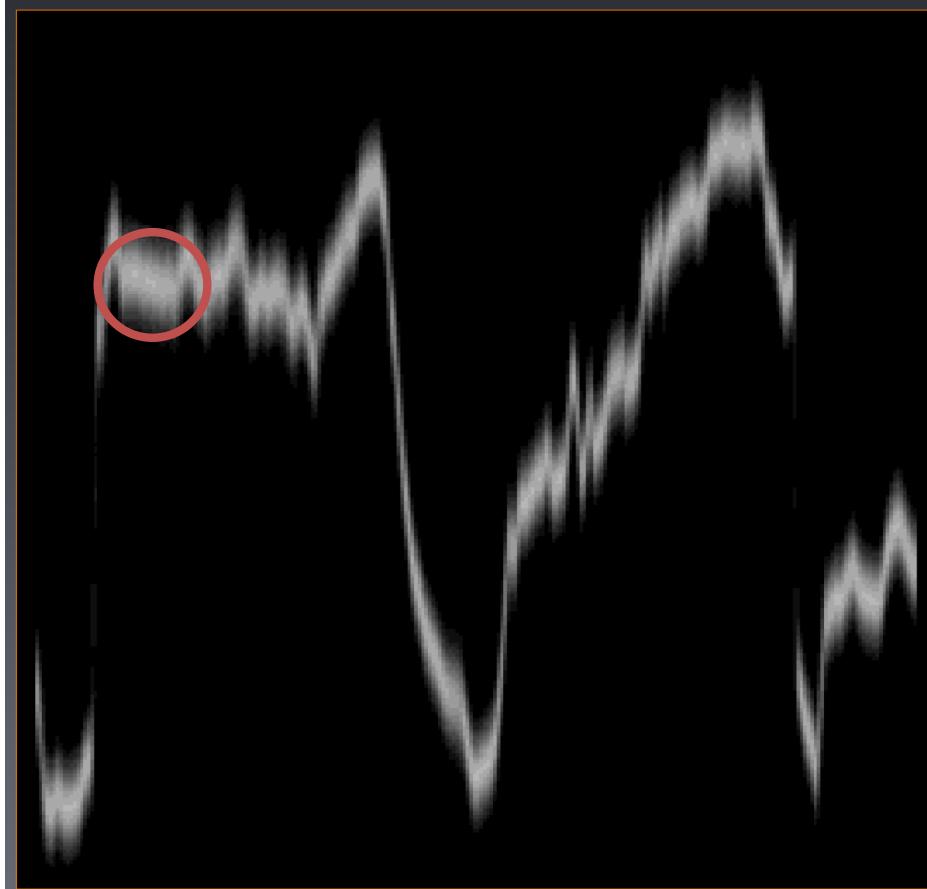


$$V(\mathbf{p}_n, r_n) = c_n \quad c_n \neq 0$$

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

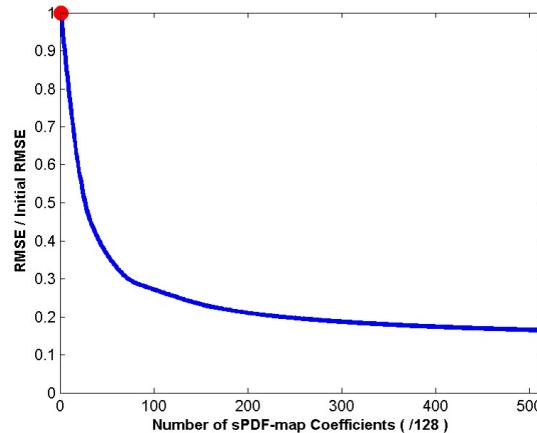
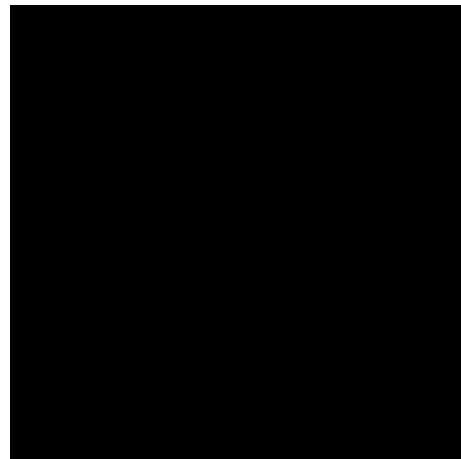


## SPATIAL AND RANGE COHERENCE

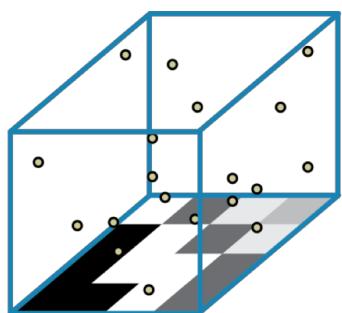




## GREEDY APPROXIMATION

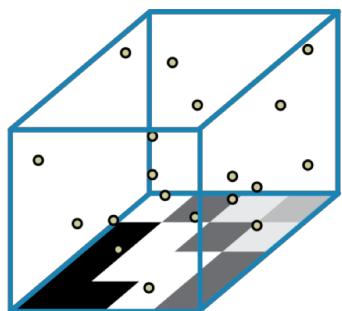
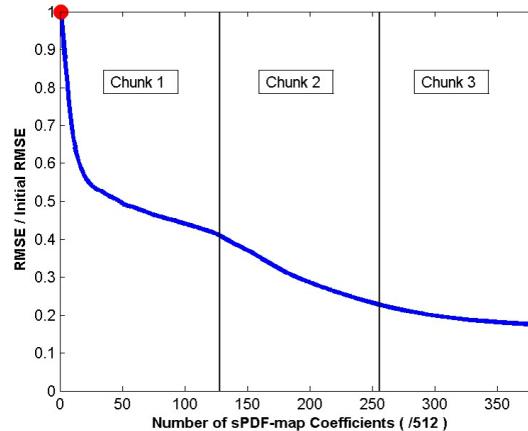
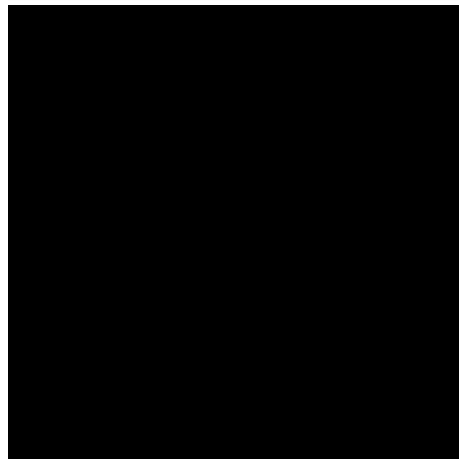


Spatial filter  $W$  :  $5 \times 5$   
1 coefficient chunk  
(# coefficients == 1 \* # pixels)





## GREEDY APPROXIMATION

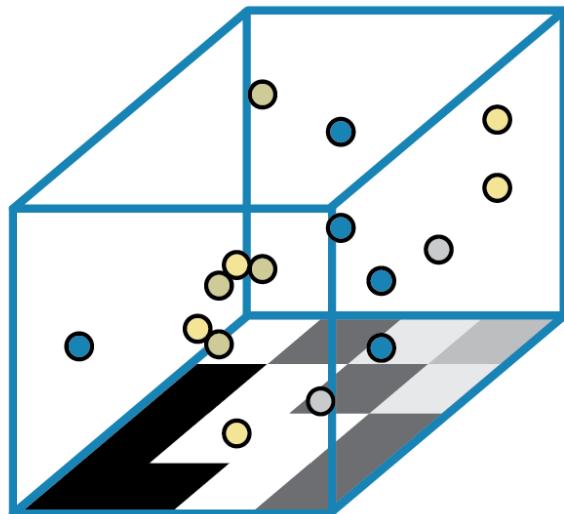


Spatial filter  $W : 3 \times 3$   
1-3 coefficient chunks  
(# coefficients == 1-3 \* # pixels)



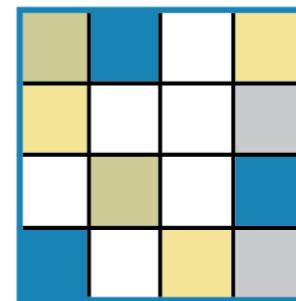
# sPDF-Maps Data Structure

## SPDF-MAPS DATA STRUCTURE



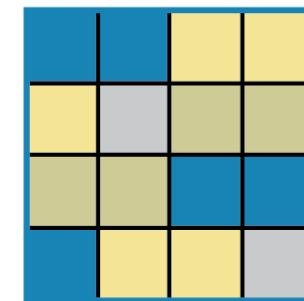
conceptual

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



index image

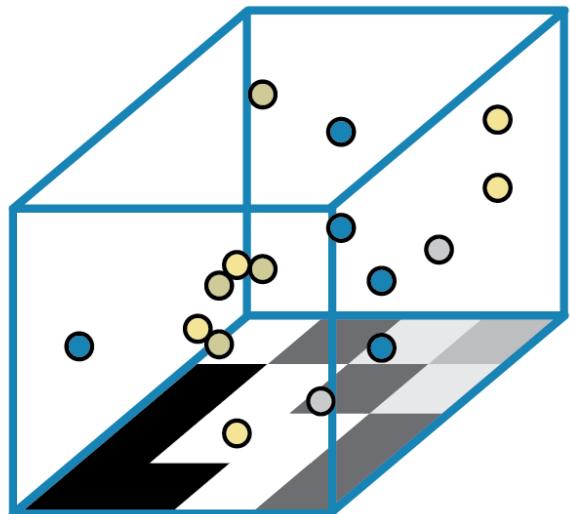
$$(index, count)_{\mathbf{p}}$$



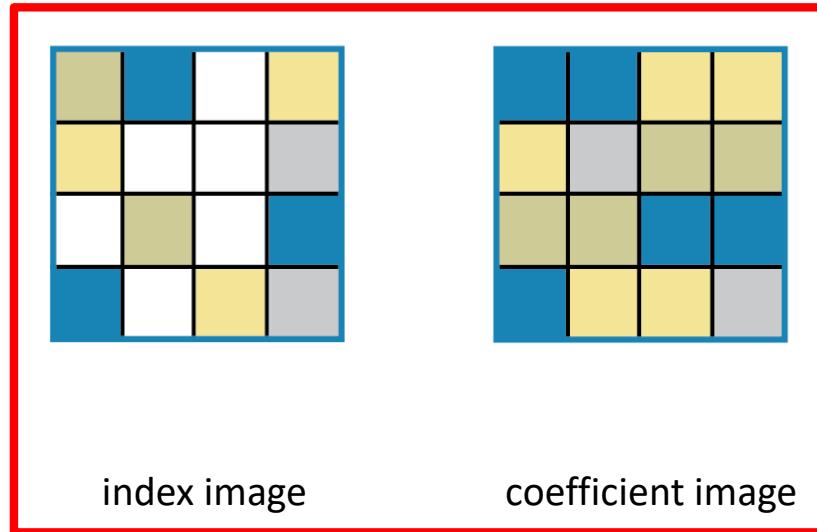
coefficient image

$$(r_n, c_n)$$

## SPDF-MAPS DATA STRUCTURE



conceptual



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

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

$$(r_n, c_n)$$

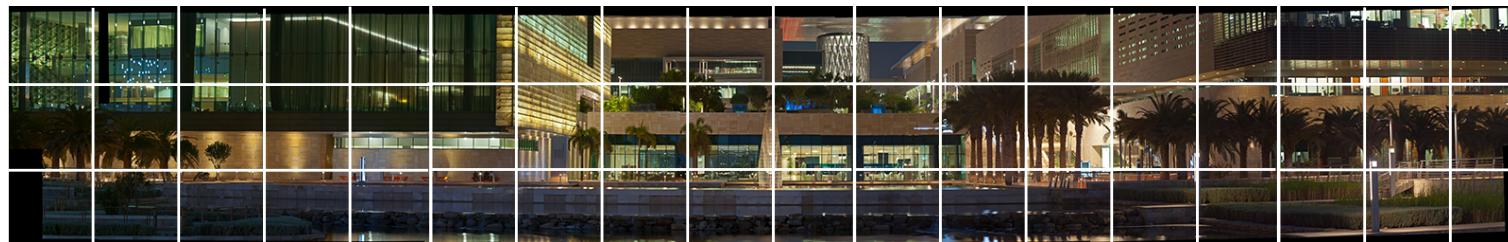


# Display-Aware Gigapixel Image Processing



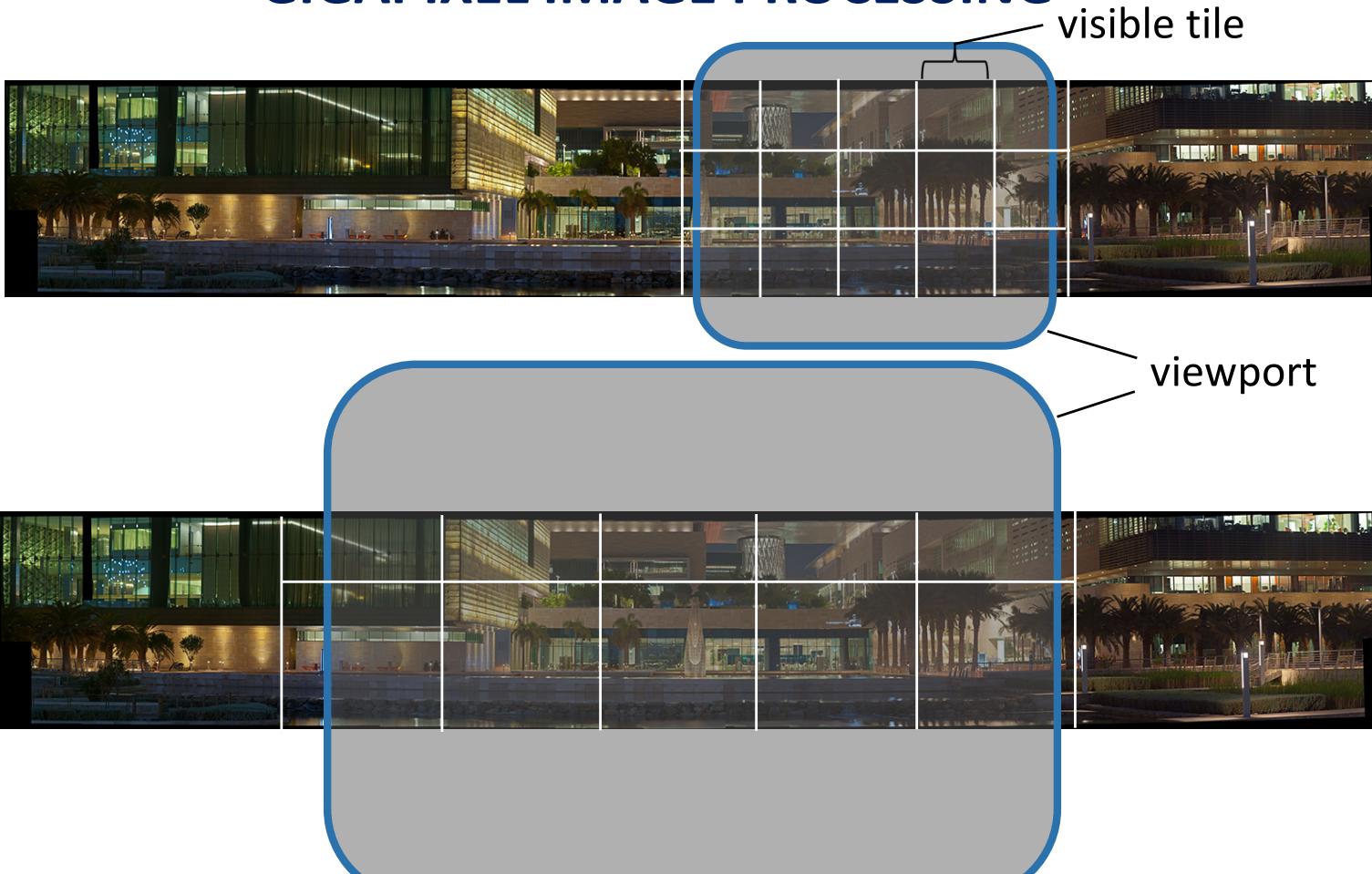
## GIGAPIXEL IMAGE PROCESSING

- 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



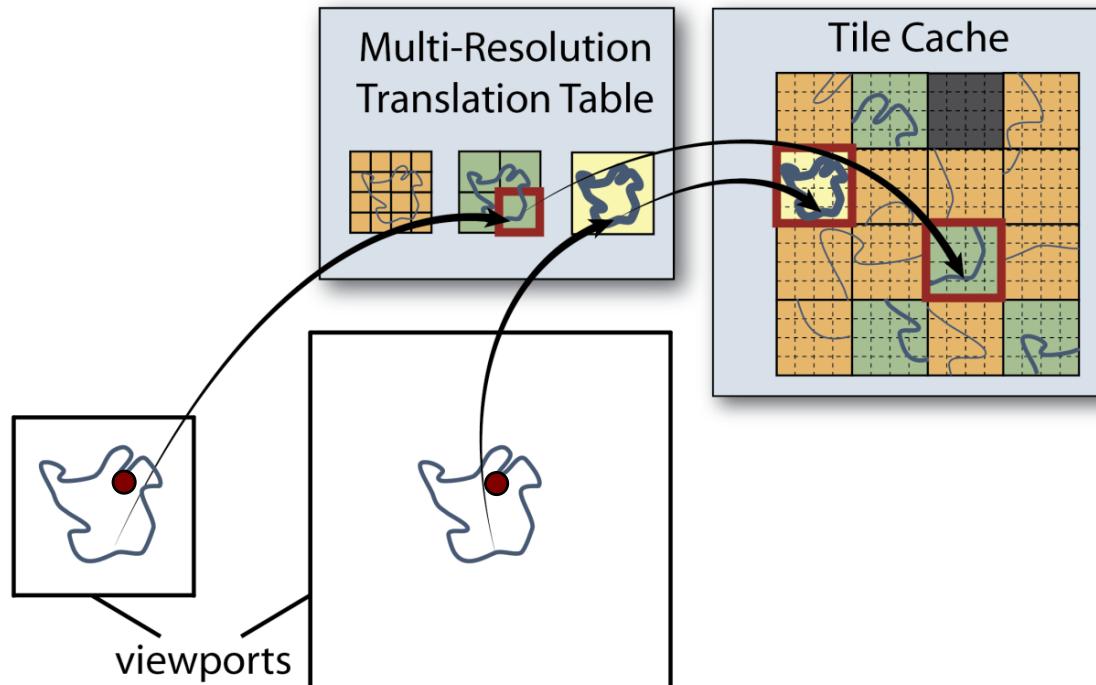


## GIGAPIXEL IMAGE PROCESSING



## GIGAPIXEL IMAGE PROCESSING

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





# Image Reconstruction

## IMAGE RECONSTRUCTION

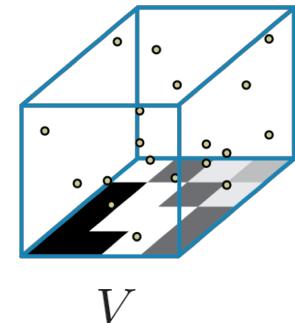
$$E [t_{\mathbf{p}} (X_{\mathbf{p}})] = \frac{1}{w_{\mathbf{p}}} \int_0^1 t_{\mathbf{p}}(r) pdf_{\mathbf{p}}(r) dr$$

- Key idea # 1  $t_{\mathbf{p}}(r) pdf_{\mathbf{p}}(r)$

Use  $t_{\mathbf{p}}(r) * K$  instead of  $\tilde{t}_{\mathbf{p}} = t_{\mathbf{p}} * K$

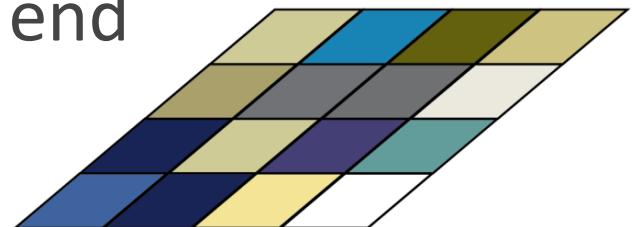
- Key idea # 2

Pre-convolve with :



## 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



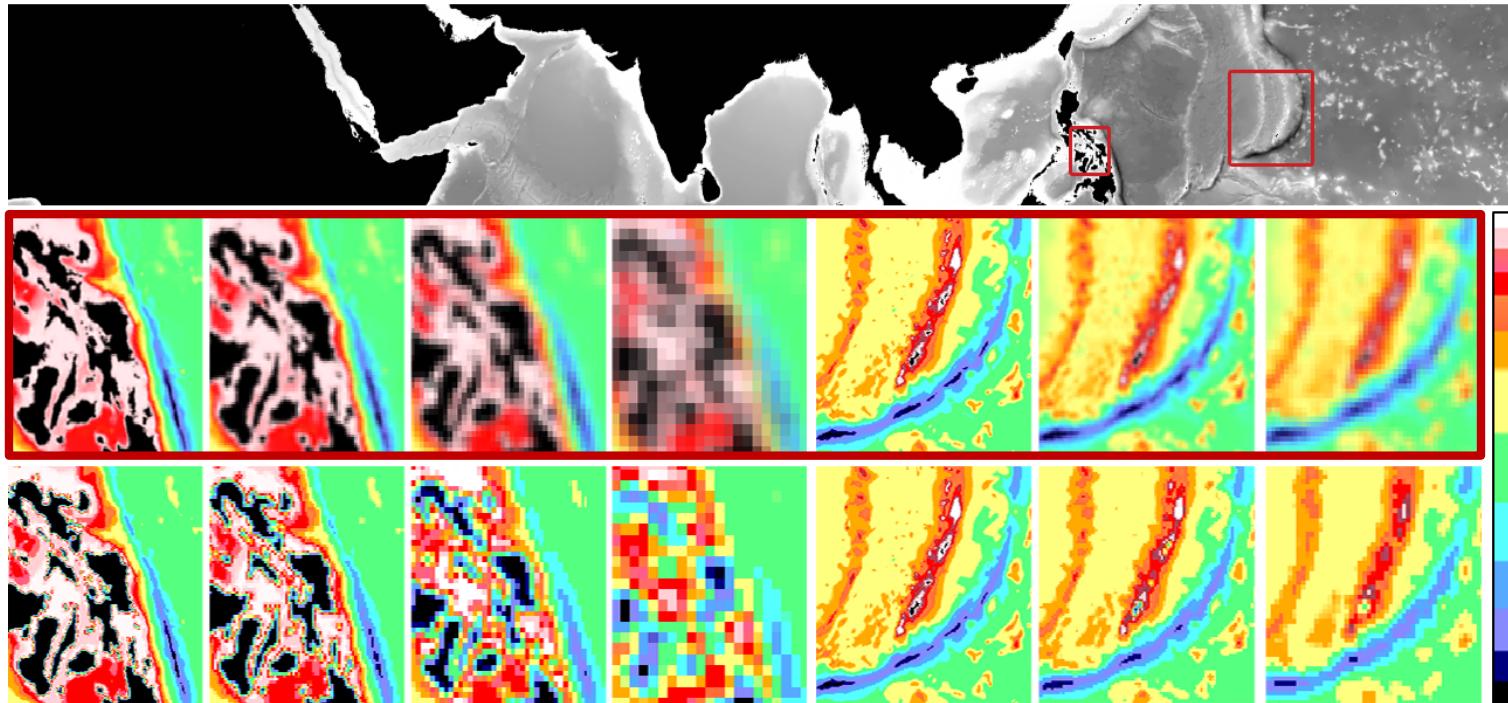
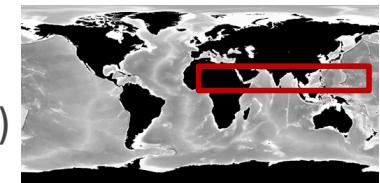


# Results



## COLOR MAPPING GIGAPIXEL IMAGES

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



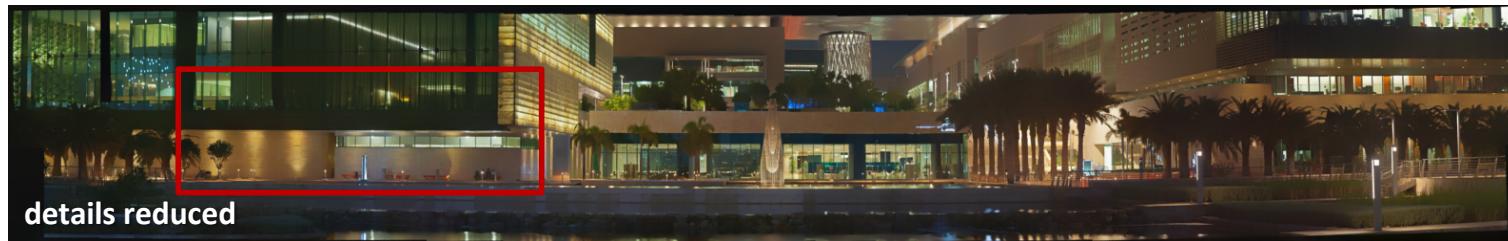




## GIGAPIXEL LOCAL LAPLACIAN FILTERING



original

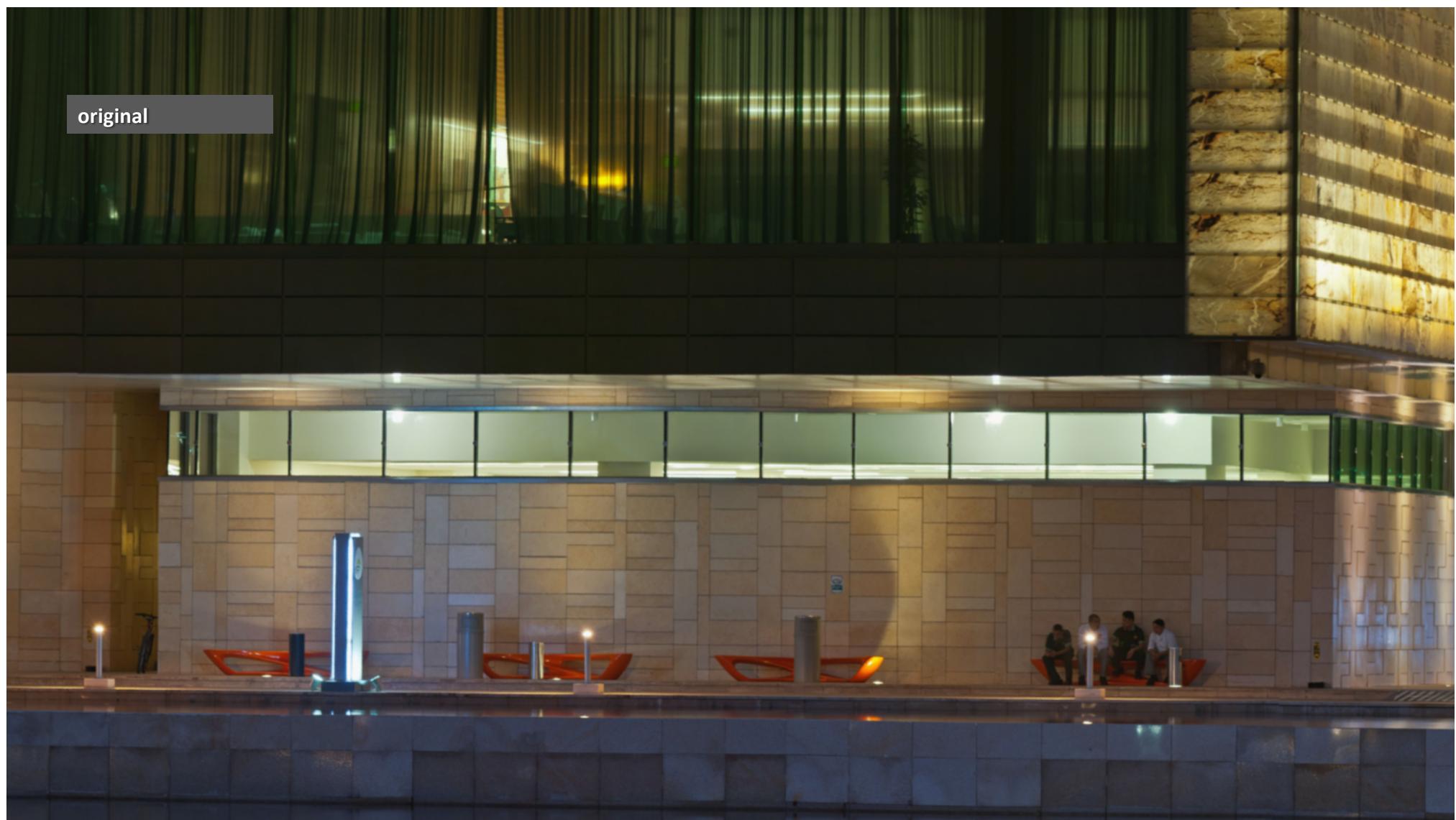


details reduced

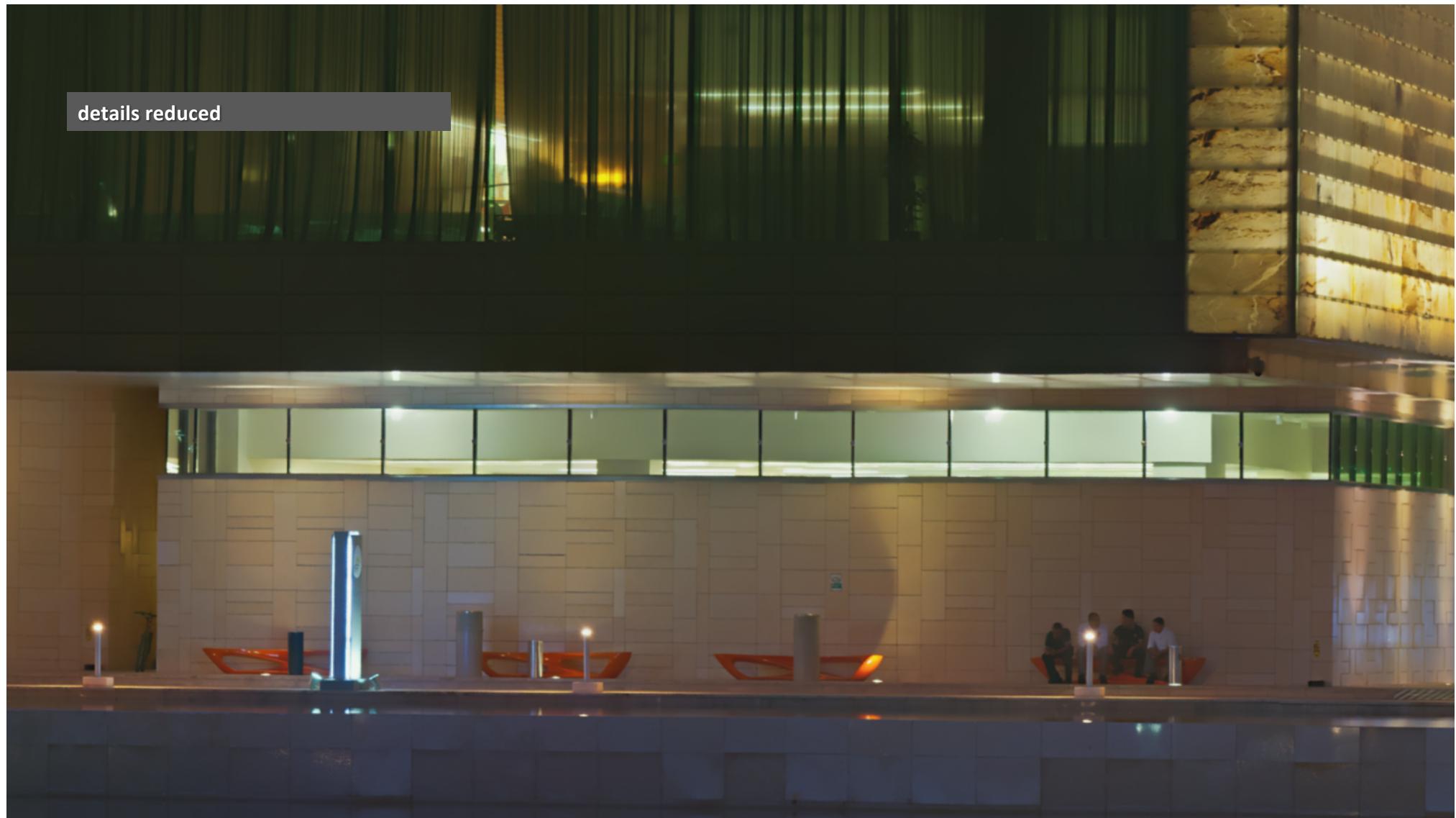


details enhanced

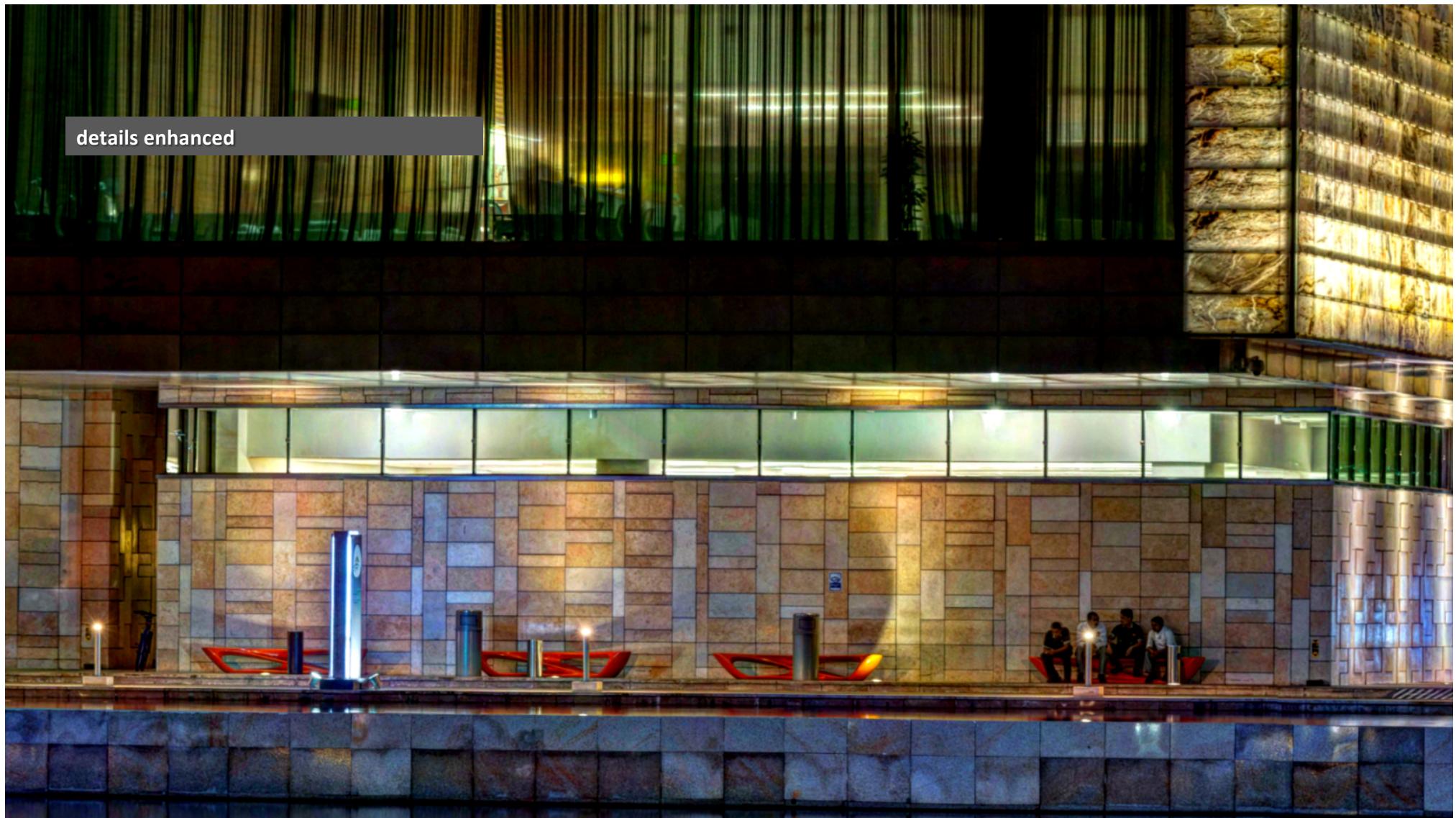
original



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



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EXHIBITION 5 – 7 December 2018  
Tokyo International Forum, Japan  
[SA2018.SIGGRAPH.ORG](http://SA2018.SIGGRAPH.ORG)

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# GPU-Based Large-Scale Scientific Visualization

**Johanna Beyer, Harvard University**

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Course Website:

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

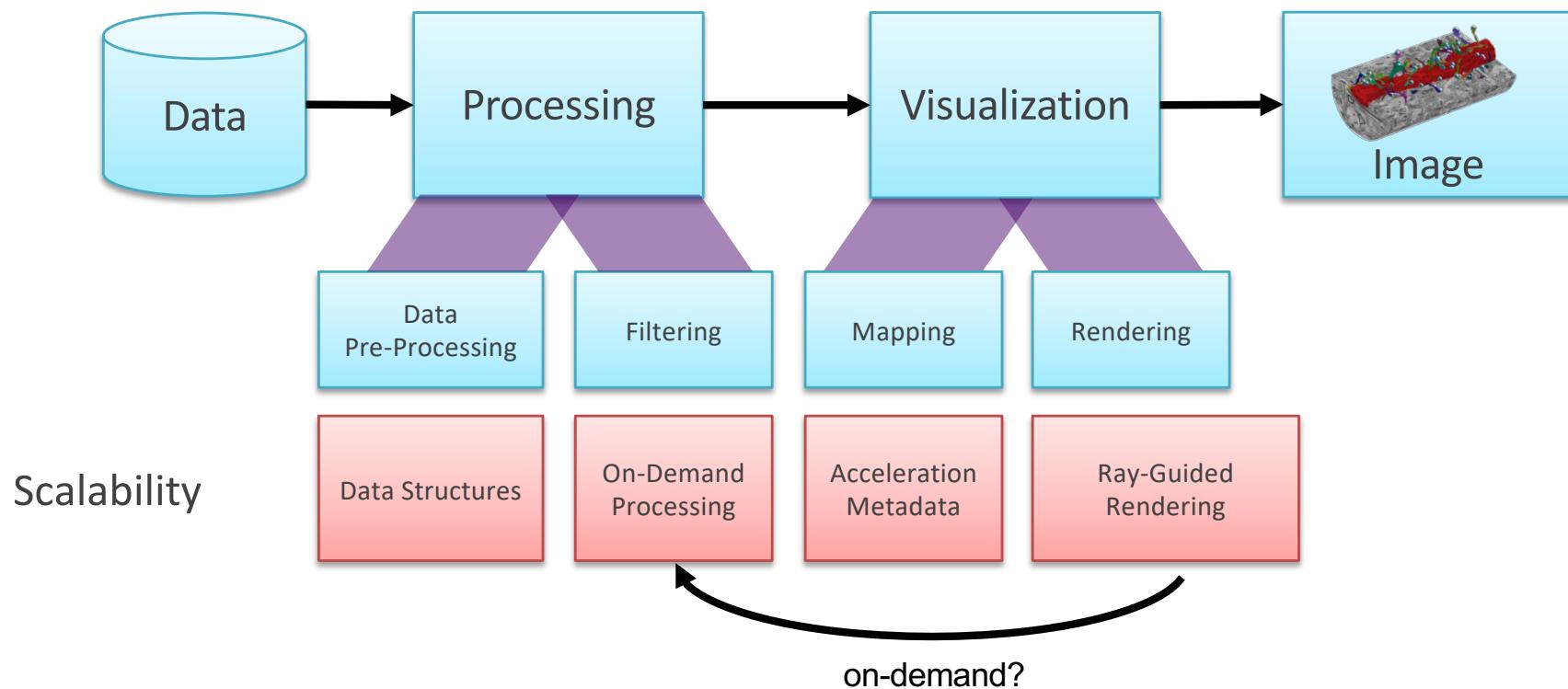




# Summary & Outlook

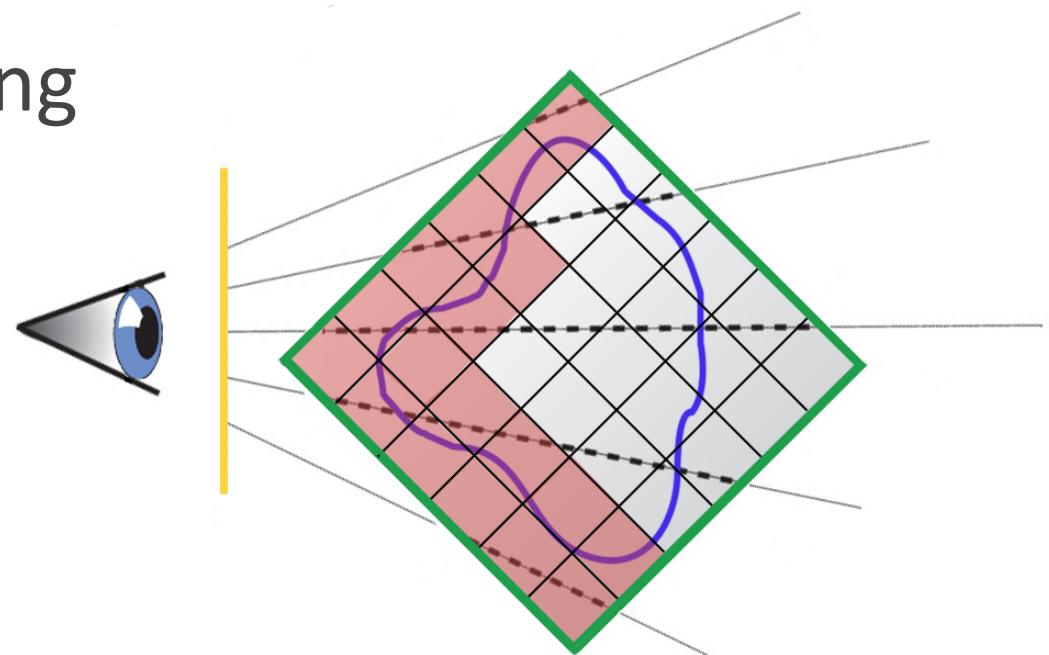


## LARGE-SCALE VISUALIZATION PIPELINE



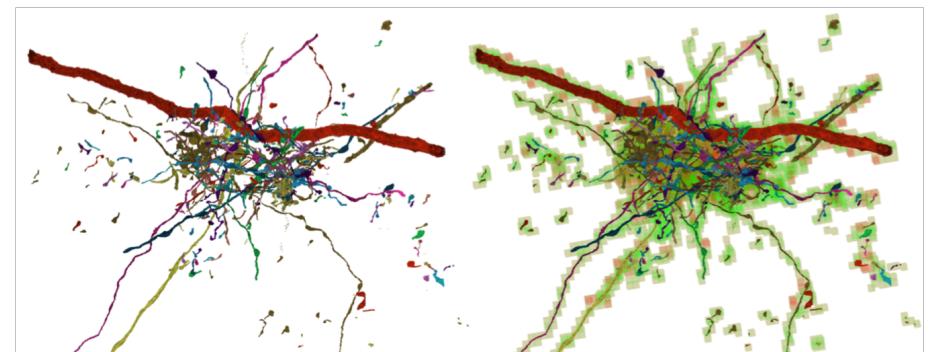
## RAY-GUIDED VOLUME RENDERING

- 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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CONFERENCE 4 - 7 December 2018  
EXHIBITION 5 - 7 December 2018  
Tokyo International Forum, Japan  
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## THANK YOU!

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