Local Statistical Filtering via Domain Dissection for Medical Imaging

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   - LA-SAS contribution
2. Locally adaptive signal-noise analysis
   - formulation
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   - analytic advance & technical challenges
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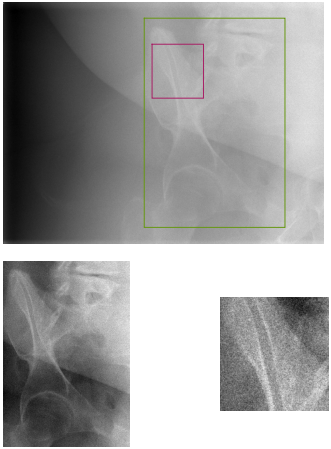
Spatially variant signal-noise analysis: needs & challenges

- Noise is prevalent in medical images
  - multiple sources (acquisition, processing, ...)
  - multiple types (Gaussian, Poisson, scatter, ...)
- Noise study: characterization & suppression
  - critical to high-fidelity analysis
    (noise propagation in processing pipeline
    e.g. gradient calculation)
  - need effective tools for systematic investigation
  - speed important for on-board imaging applications
- Challenging conditions
  - valuable low-contrast content (especially in CT)
  - acquisition constraints (resolution, imaging dose)
  - motion: nonlinear intensity-deformation relationship
  - ⋆ spatial variance
    (w.r.t. material, density, acquisition set-up)

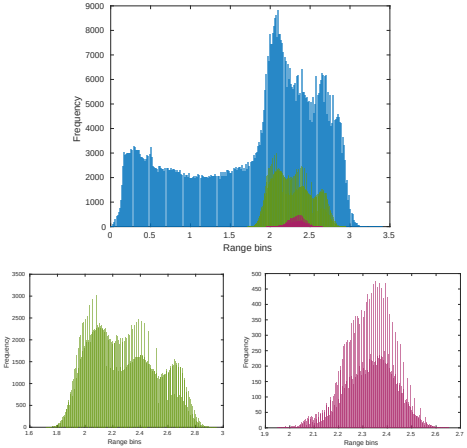


pelvis cone-beam OBI
(125 kV, coronal projection)
with spatially variant scattering

Spatially variant signal-noise analysis: contribution

- LA-SAS
  (locally adaptive signal-noise analysis system)
  - revealing local noise statistics and signal structure
  - filtering in adaptation to local structures
  - enabling effective noise suppression

- LA-SAS design and development
  - basic operations
  - versatile filter composition
  - CUDA LA-SAS (efficiency)



range histograms: global region (top)
vs. nested sub-regions (bottom)

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Locally adaptive signal-noise analysis: problem description

- Dual task of an analysis/filtering mechanism (F)

$$I(\mathbf{x}) = \hat{I}(\mathbf{x}) + \eta(\mathbf{x}), \qquad \mathbf{x} \in \Omega \subset \mathbb{R}^D$$

  - detect/reconstruct unknown signal, $\hat{I}$
  - estimate/suppress unknown noise, η

- Adaptation to local variation

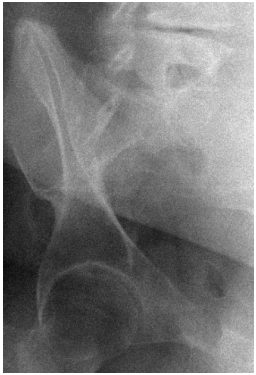
$$\hat{I}(\mathbf{x}) := \sum_{\mathbf{x}' \in \mathcal{N}(\mathbf{x})} F\Big(\mathbf{x}', I(\mathbf{x}');\ p_{\mathcal{N}(\mathbf{x})}\Big)$$

  - based on local statistics, $p_{\mathcal{N}(\mathbf{x})}$, over spatial neighborhood, $\mathcal{N}(\mathbf{x})$ (mean, median, deviation, range distribution, etc)
  - preserving signal structure (smooth subregions, discontinuities at region boundaries, etc)

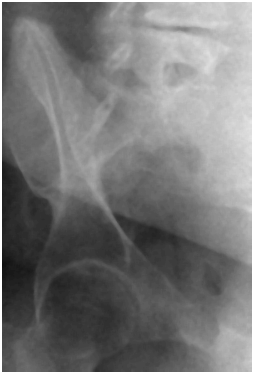
Locally adaptive filtering example: median

$$\hat{I}(\mathbf{x}) = p_{\mathcal{N}(\mathbf{x})} = \underset{\mathcal{N}(\mathbf{x})}{\text{median}}\{I(\mathbf{x})\}$$

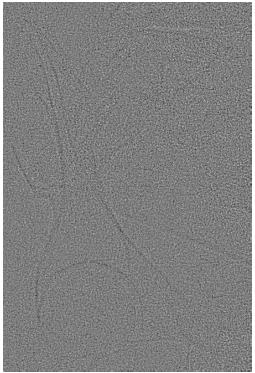
- basic denoising & processing sub-module



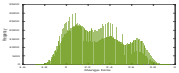
(regional dynamic range)



median filter output (5×5)



residual image



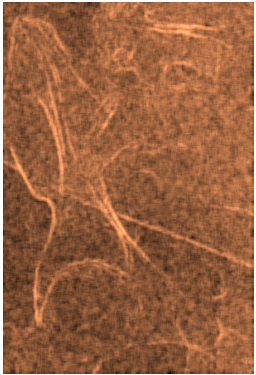
Chung *et al.* *NSS/MIC*, 2010

Locally adaptive filtering example: entropy

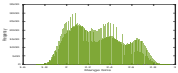
$$p_{\mathcal{N}(\mathbf{x})} = \mathrm{Pr}_{\mathcal{N}(\mathbf{x})}\{I(\mathbf{x})\}$$
$$H(\mathbf{x}) = -\sum p_{\mathcal{N}(\mathbf{x})} \log(p_{\mathcal{N}(\mathbf{x})})$$

- multimodal registration
- basic step for other processing modules (e.g. segmentation, histogram equalization)

(regional dynamic range)



local entropy map (9×9)



Zhang *et al.* *ICBBE*, 2008 Pluim *et al.* *IEEE TMI* (22), 2003

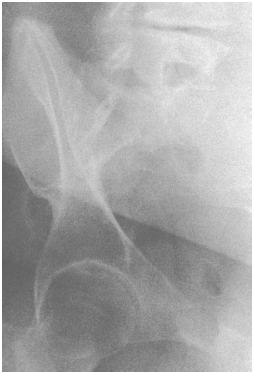
Locally adaptive filtering example: histogram equalization (HE)

$$p_{\mathcal{N}(\mathbf{x})} = \text{hist}[r, I(\mathcal{N}(\mathbf{x}))]$$

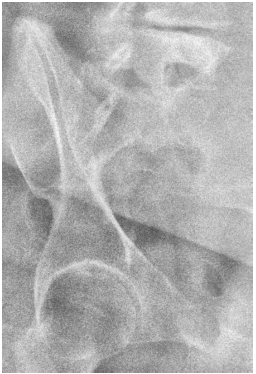
where hist: local histogram
r: quantized ranges

- local contrast enhancement
- local + global distribution information

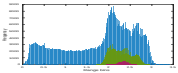
(global dynamic range)



global HE



local HE (`adapthisteq`)
to be replaced with overlapping LHE



Zhu *et al.* *CVIA* (73), 1999

Locally adaptive filtering example: bilateral filter (BF)

$$p_{\mathcal{N}(\mathbf{x})} = \sigma_r(\mathbf{x})$$

$$k_s(\mathbf{x}, \mathbf{x}') = e^{-\frac{\|\mathbf{x}-\mathbf{x}'\|_2^2}{\sigma_s^2}}$$

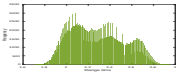
$$k_r(I(\mathbf{x}), I(\mathbf{x}')) = e^{-\frac{\|I(\mathbf{x})-I(\mathbf{x}')\|_2^2}{\sigma_r^2(\mathbf{x})}}$$

(space- and range-kernels)

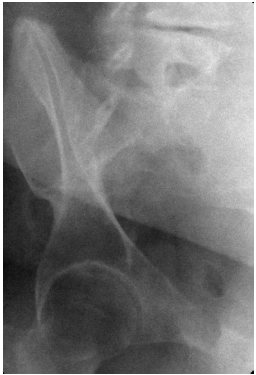
- boundary-preserving denoising
- local adaptation to boundary "jumps"

Tomasi & Manduchi. *ICCV*, 1998

(regional dynamic range)



global BF
$\sigma_s = 1.5, \sigma_r = 0.157$



locally adaptive BF
$\sigma_s = 1.5,$
$\sigma_r(\mathbf{x}) = \mathrm{mad}(\mathcal{N}_{9\times 9}(\mathbf{x}))$

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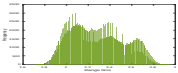
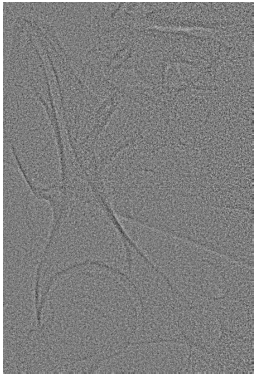
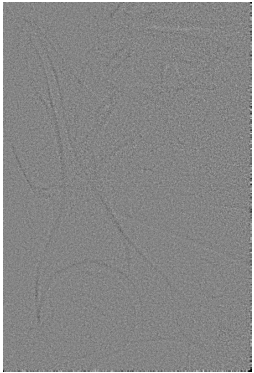




global BF
$\sigma_s = 1.5, \sigma_r = 0.157$
(residual image)



locally adaptive BF
$\sigma_s = 1.5,$
$\sigma_r(\mathbf{x}) = \mathrm{mad}(\mathcal{N}_{9\times 9}(\mathbf{x}))$
(residual image)

Locally adaptive filtering: analytic advance & technical challenges

- Reveal and preserve spatially variant signal structure
  (same as in conventional methods with spatial adaptivity)
- Permit spatially inhomogeneous noise behavior
  (often observed in medical imaging)
- Depart from filtering algorithms with predetermined, global parameters
  (including histograms and some bilateral filters)

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  (algorithmic complexity, concurrency, numerical behavior)

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- Fully parallel but highly redundant
- Work-efficient may become
  - highly sequential
  - highly divergent
  - numerically unstable
- Compromises:
  increase redundancy to stabilize numerics and expose parallelism

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LA-SAS design principles

- Multi-layer configuration between
  - filtering at the application level (top)
  - parallel computing at the architecture level (bottom)

  (not one-to-all cross-bar configuration)

- Abstraction of basic LA-SAS operations & versatile filter composition

- Enabling systematic investigation & efficient implementation

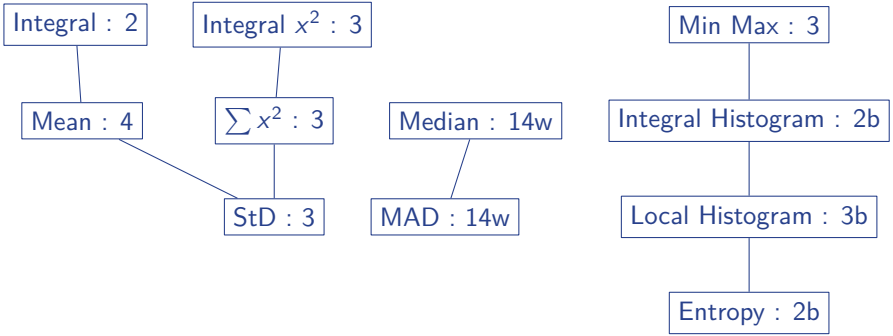
- Domain dissection
- Locality adaptation
  - Local range per tile
- Redundancy reduction
  - Single-pass precomputation
  - Common sub-regions

LA-SAS MATLAB Syntax and Pyramid Data Structure

```
                  Mean
                  Std
                  Min
                  Max
locStat = local { Median } [ (Image, b)
                  Mad        Tile(Image, b, t)
                  Hist       Tile1x1(Image, b) ]
                  Entropy
```

```
localStat
 ├── image
 ├── integral
 ├── integral2
 ├── minLocal
 ├── maxLocal
 ├── integralHistogram
 ├── min
 ├── max
 ├── tile{1}
 │    ├── size
 │    ├── integral
 │    ├── integral2
 │    ├── minLocal
 │    ├── maxLocal
 │    ├── integralHistogram
 │    ├── min
 │    └── max
 └── tile{2}
      └── size
etc
```

LA-SAS Dependency Graph and Arithmetic Complexity

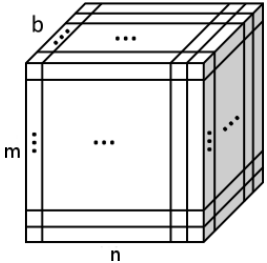


operations per image pixel

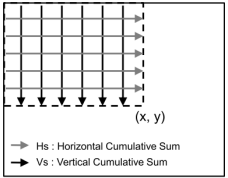
w : number of pixels in a local neighborhood

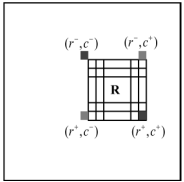
b : number of histogram bins

LA-SAS primitives: local grid for local histograms in constant time



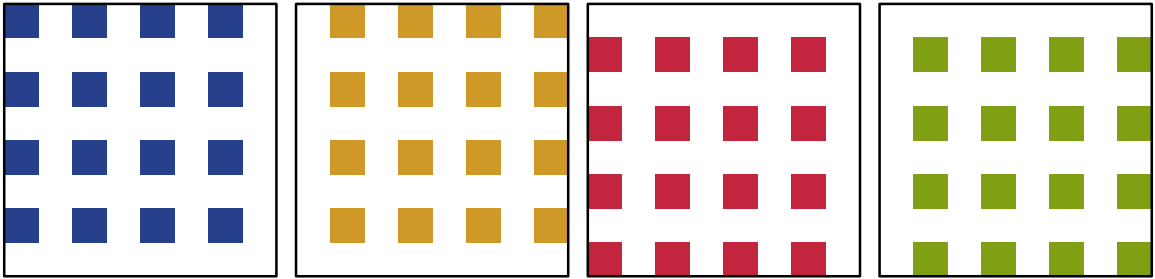
$(D+1)$-dimensional grid embedding, with local dynamic range bins





Histograms in constant time from integral histogram representation (Poostchi *et al*, *ACCVW*, 2012))

Domain dissection: local adaptivity & global concurrency



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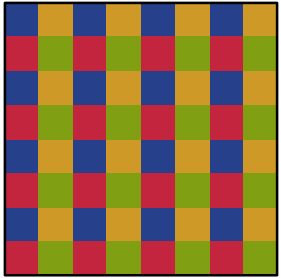
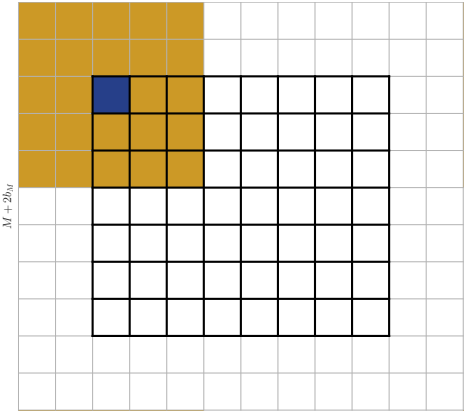


Domain dissection: local adaptivity & global concurrency



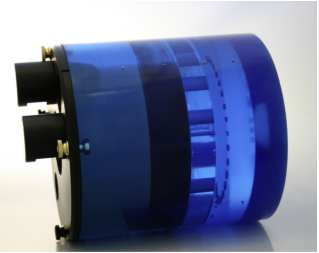
Sliding window operation

LA-SAS Implementation

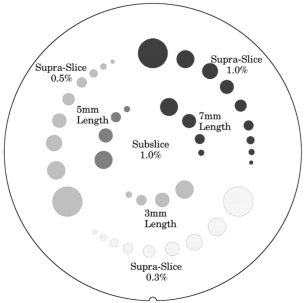
- Utilize MATLAB built-ins
- Data in `gpuArray`
- CUDA kernels for the rest
- Compute all you can in each pass
- Cache computed results in cell array of struct to reuse (memoization)
- User responsible for caching and data motion to/from GPU

- Three CUDA kernels:
  - `localStats`
  - `histPrefixSum`
  - `localMinMax`
- Tiles mapped on grid
- Thread blocks working locally
- Common neighborhood shared

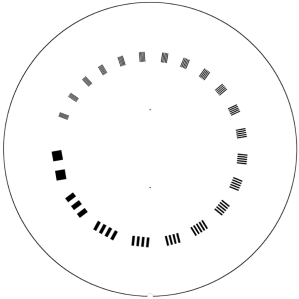
Catphan Phantom



Catphan 504 phantom by Varian Medical Systems

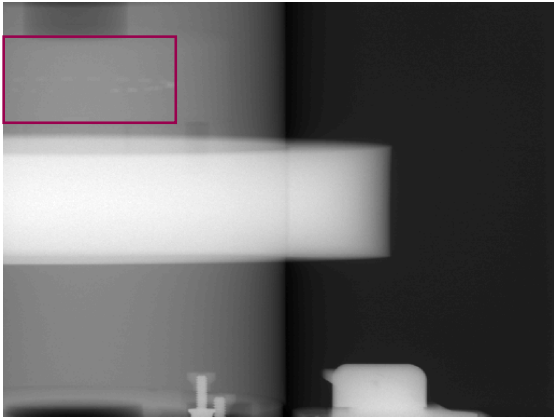


CTP515 low contrast module with supra-slice and subslice contrast targetss

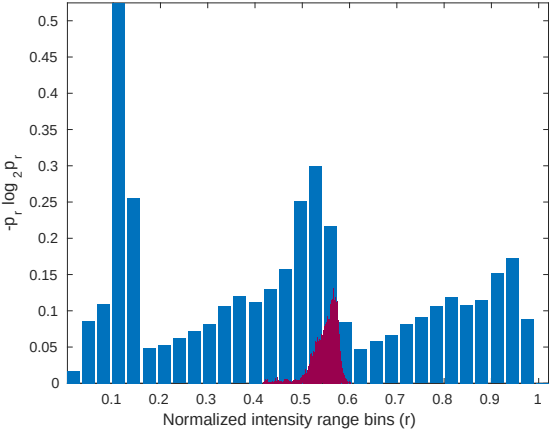


CTP528 High resolution module with 21 line pair per cm gauge and point source

Local statistics exploration

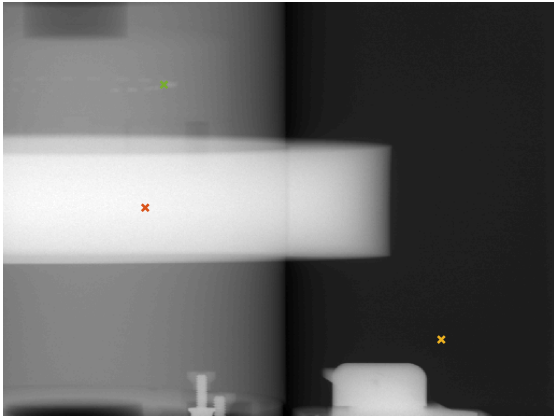


Catphan cone-beam 125kV X-ray ($\theta = 21^o$)

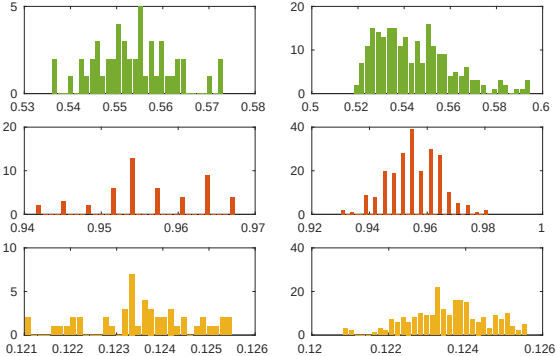


global and ROI-specific 32-bin Shannon distributions

Local statistics exploration



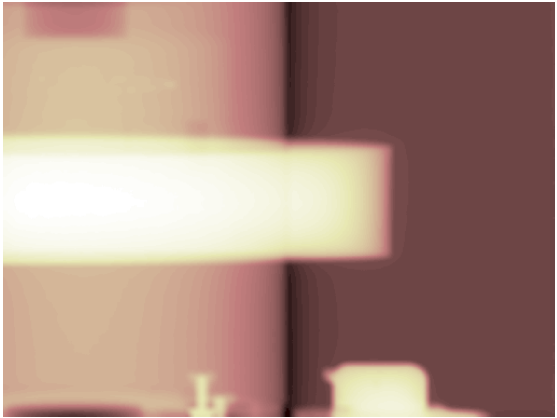
Catphan cone-beam projection example histogram windows (7×7)



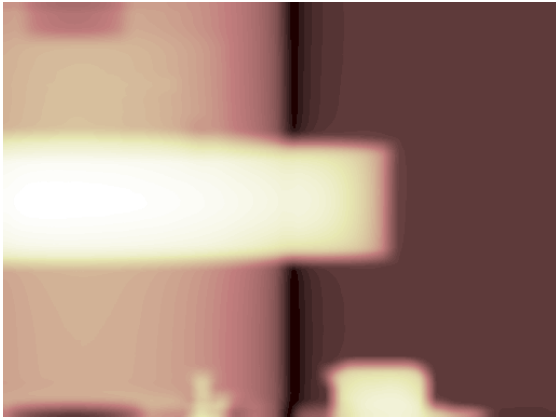
(7×7) (15×15)

example 32-bin local histograms

Local statistics exploration

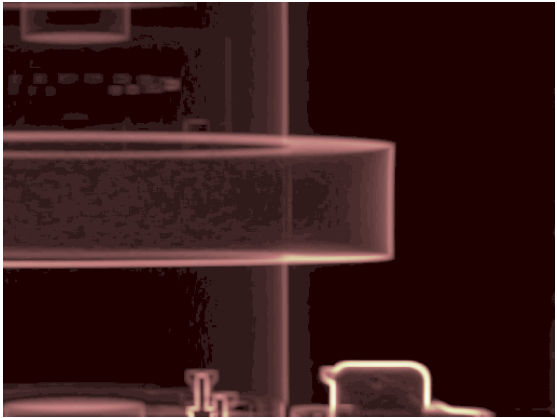


7×7 mean

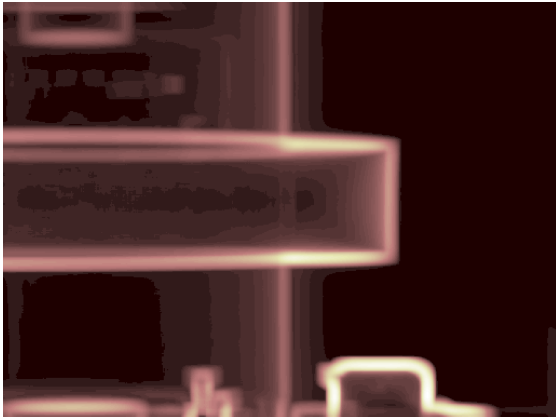


15×15 mean

Local statistics exploration

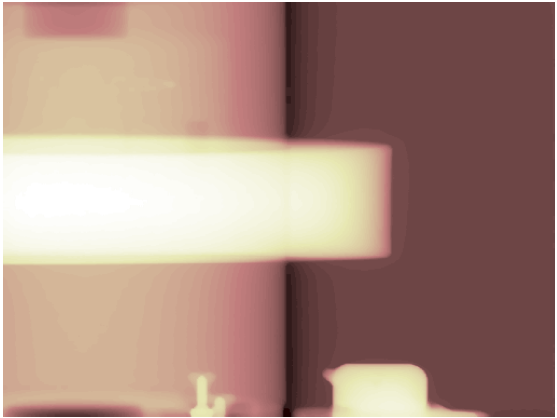


7×7 standard deviation

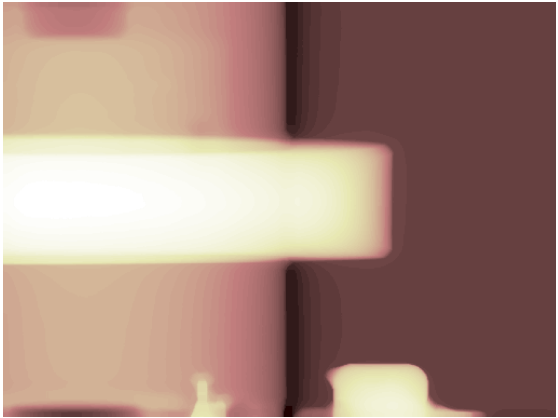


15×15 standard deviation

Local statistics exploration



7×7 median



15×15 median

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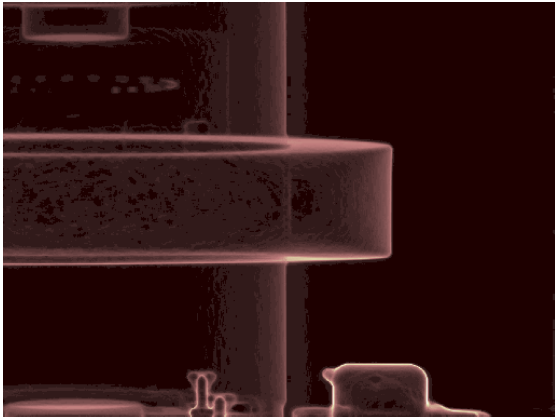
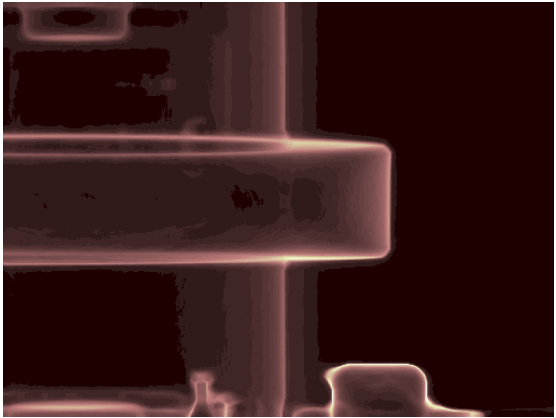
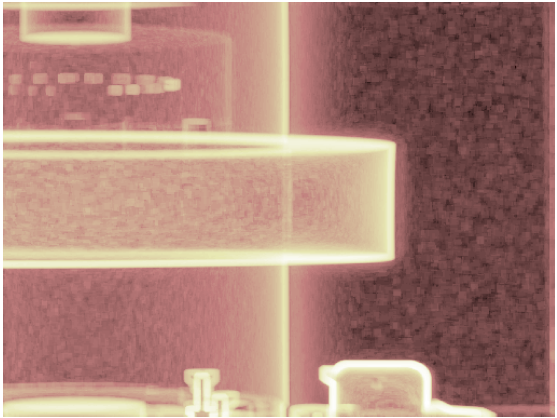


7×7 median absolute deviation (MAD)

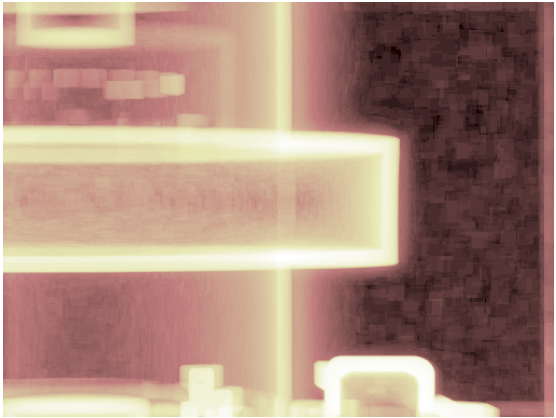


15×15 median absolute deviation (MAD)

Local statistics exploration

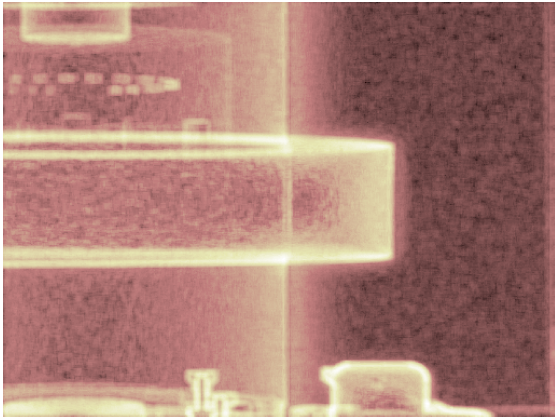


7×7 dynamic range (log-scale)

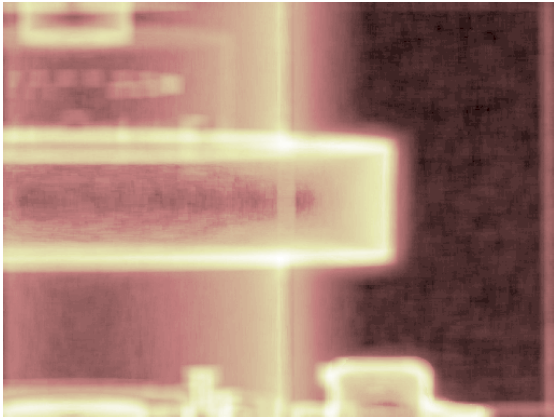


15×15 dynamic range (log-scale)

Local statistics exploration

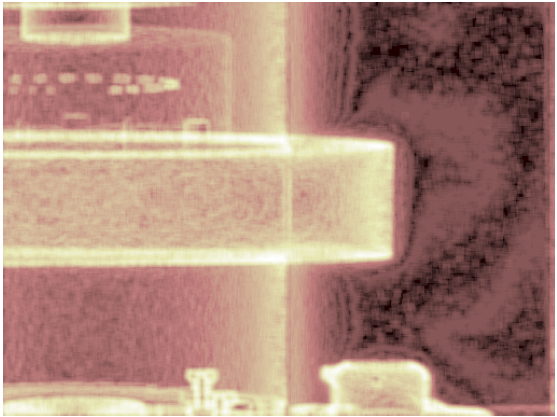


7×7 entropy via locally adaptive 32-bin histograms



15×15 entropy via locally adaptive 32-bin histograms

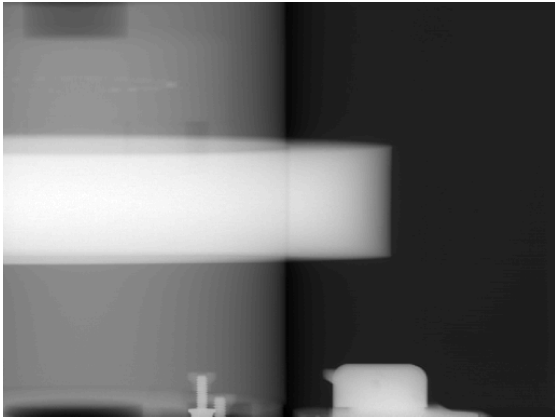
Local statistics exploration



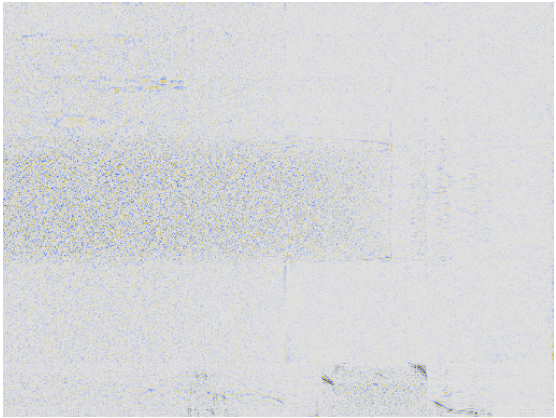
7×7 entropy via uniform 256-bin histogram

15×15 entropy via uniform 256-bin histogram

Local statistics exploration

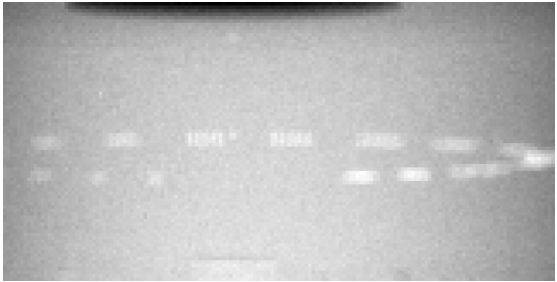


global SVD filtering (50 out of 384 components)

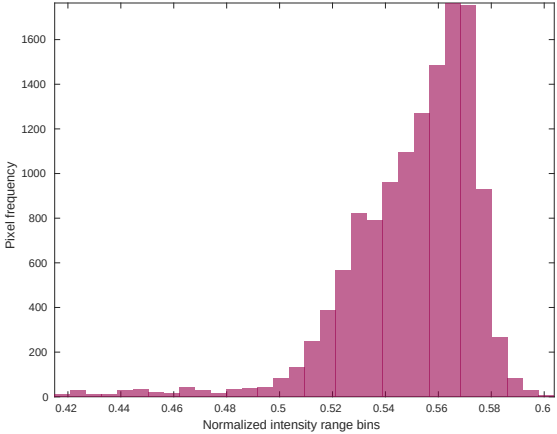


global SVD residual (50 out of 384 components)

Local statistics exploration: ROI detail



Catphan cone-beam 125kV X-ray ($\theta = 21^o$)



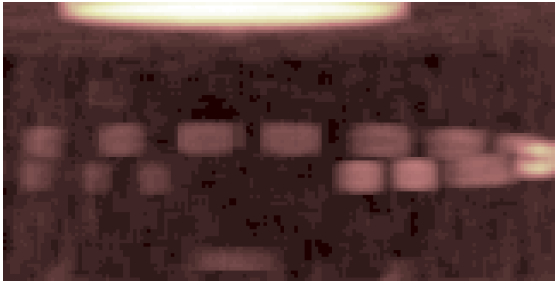
global and ROI-specific 32-bin histograms

Local statistics exploration: ROI detail

7×7 mean

15×15 mean

Local statistics exploration: ROI detail



7×7 standard deviation

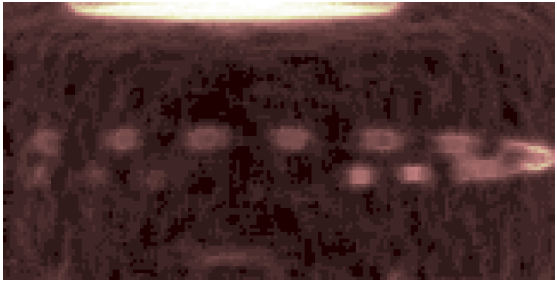
15×15 standard deviation

Local statistics exploration: ROI detail

7×7 median

15×15 median

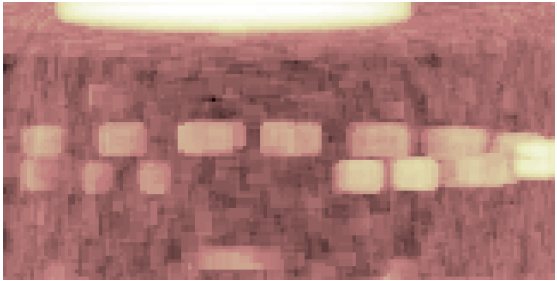
Local statistics exploration: ROI detail



7×7 median absolute deviation (MAD)

15×15 median absolute deviation (MAD)

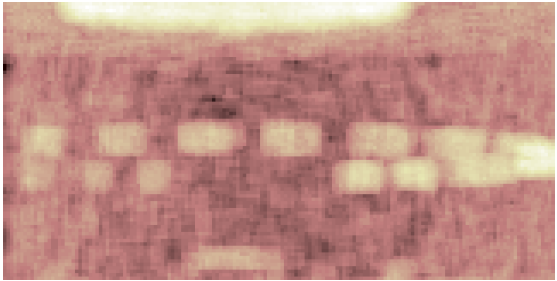
Local statistics exploration: ROI detail



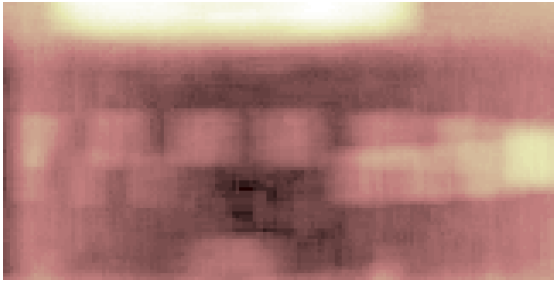
7×7 dynamic range (log-scale)

15×15 dynamic range (log-scale)

Local statistics exploration: ROI detail

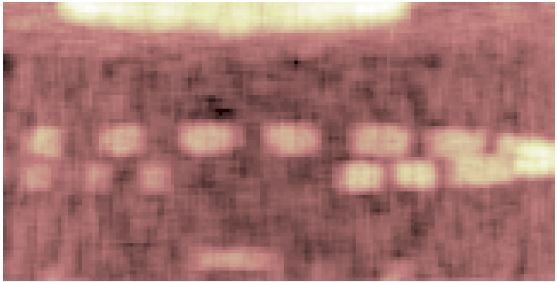


7×7 entropy via locally adaptive 32-bin histograms

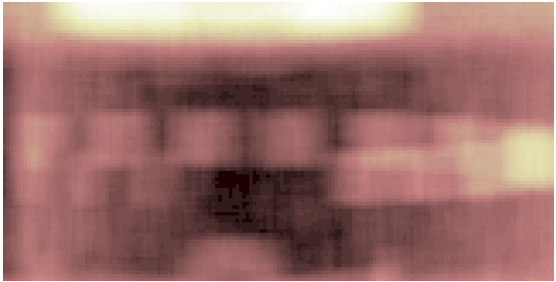


15×15 entropy via locally adaptive 32-bin histograms

Local statistics exploration: ROI detail

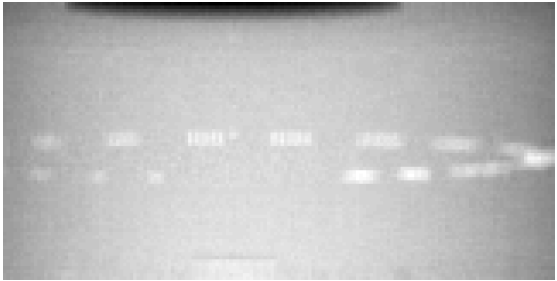


7×7 entropy via uniform 256-bin histogram

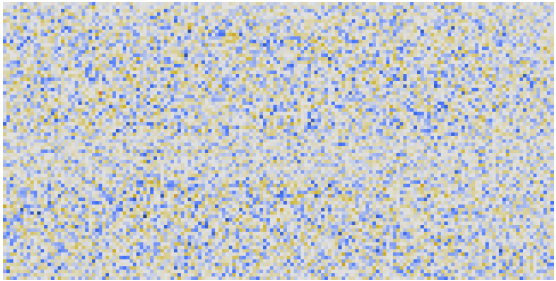


15×15 entropy via uniform 256-bin histogram

Local statistics exploration: ROI detail



regional SVD filtering (20 out of 80 components)

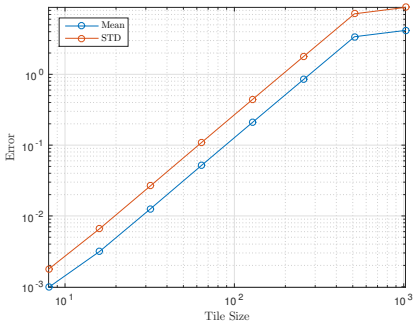


regional SVD residual (20 out of 80 components)

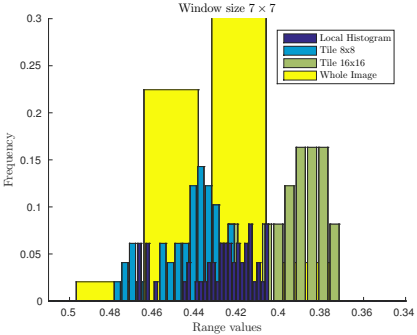
Accuracy Results

CPU: 4 x AMD Opteron(tm) Processor 6376 @ 2.3 GHz (4 x 16 cores), 128 GB DDR3
GPU: NVIDIA Tesla K20c, 13 SMs @ 0.7 GHz (13 x 192 = 2496 cores), 5 GB GDDR5

Single precision error in Mean and STD for 1000x1000 image



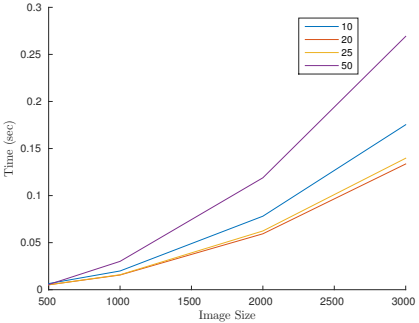
Histogram difference for same ROI



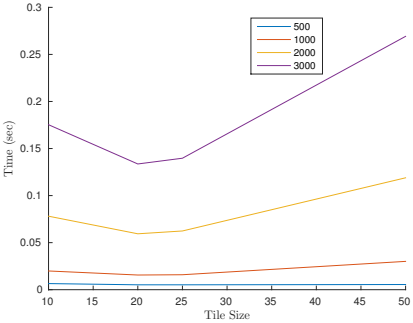
Timing Results

LA-SAS kernels precomputations with different image-tile sizes

Timing results for different tile sizes

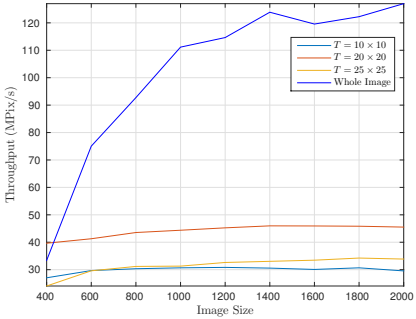


Timing results for different image sizes

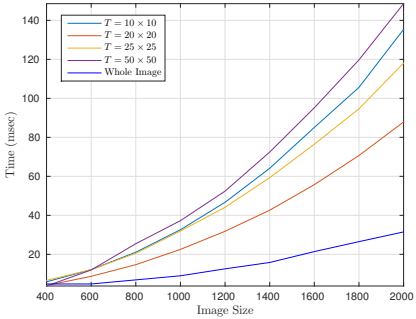


Timing Results

Throughput results for different image sizes

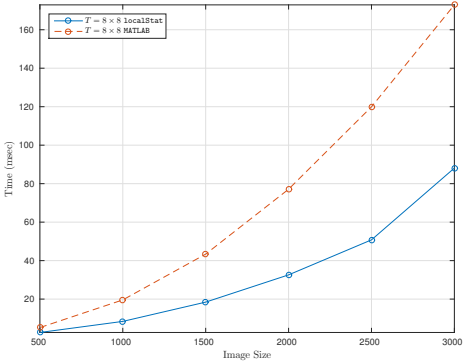


Timing results for different image sizes

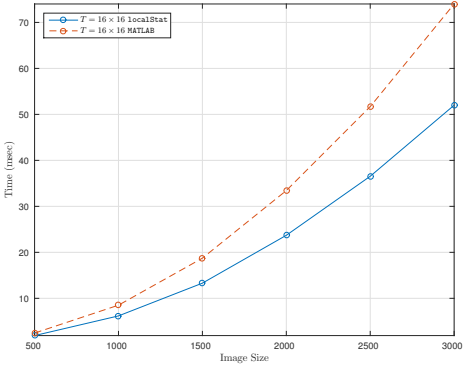


localStat: vs MATLAB GPU

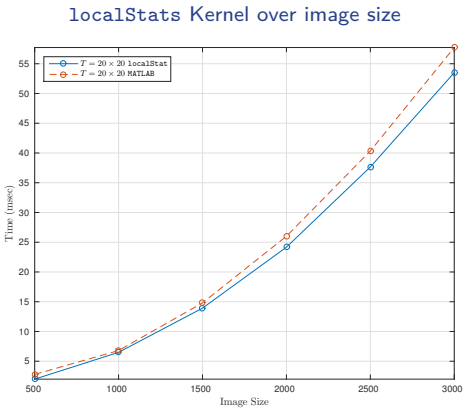
localStats Kernel over image size

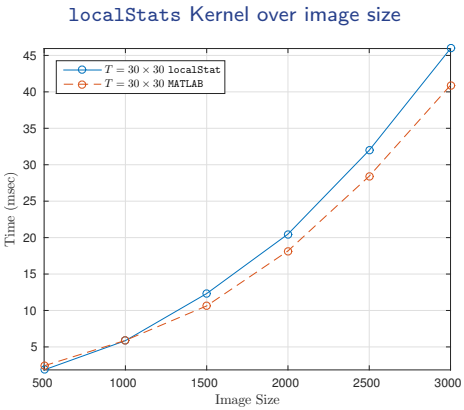


localStats Kernel over image size



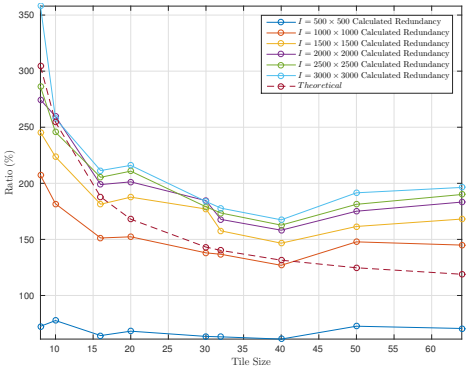
Timing Results



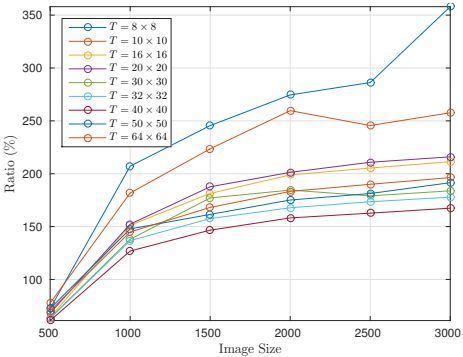


Timing Results

Timing ratio between whole image and tile for `localStats`

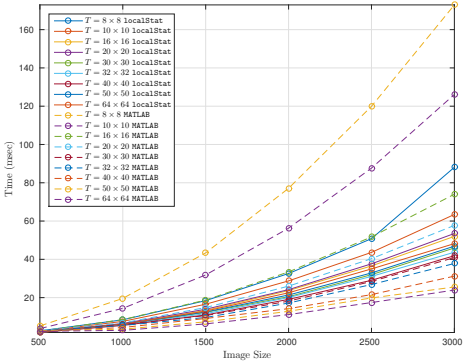


Timing ratio between whole image and tile for `localStats`

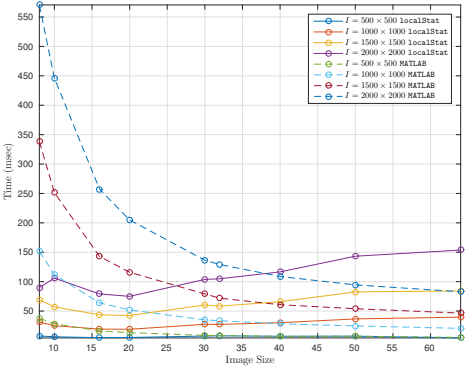


Timing Results

Multiple kernels all timings



Timing for histogram prefix sum



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