Local Statistical Filtering via Domain Dissection for Medical Imaging

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Alexandros-Stavros Iliopoulos\textsuperscript{1}  Dimitris Floros\textsuperscript{2}  Nikos Pitsianis\textsuperscript{2,1}  Xiaobai Sun\textsuperscript{1}
Fang-Fang Yin\textsuperscript{3}  Lei Ren\textsuperscript{3}

\textsuperscript{1}Department of Computer Science, Duke University
\textsuperscript{2}Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki
\textsuperscript{3}Department of Radiation Oncology, Duke University School of Medicine

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Spatially variant signal-noise analysis: motivation
needs & challenges
LA-SAS contribution

Locally adaptive signal-noise analysis
formulation
example filters
analytic advance & technical challenges

LA-SAS: design & development
design principle: multi-layer configuration
domain dissection: local adaptivity & global concurrency
CUDA LA-SAS
experimental results

Recap & discussion

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1 Spatially variant signal-noise analysis: motivation
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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 \((F)\)

\[
l(x) = \hat{l}(x) + \eta(x), \quad x \in \Omega \subset \mathbb{R}^D
\]

- detect/reconstruct unknown signal, \(\hat{l}\)
- estimate/suppress unknown noise, \(\eta\)

- Adaptation to local variation

\[
\hat{l}(x) := \sum_{x' \in \mathcal{N}(x)} F(x', l(x'); p_{\mathcal{N}(x)})
\]

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

\[ \hat{I}(x) = p_{\mathcal{N}(x)} = \text{median}\{ I(x) \} \]

- 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

\[ p_N(x) = \Pr_N \{ l(x) \} \]
\[ H(x) = - \sum p_N(x) \log(p_N(x)) \]

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

Zhang et al. *ICBBE*, 2008  
Pluim et al. *IEEE TMI* (22), 2003
Locally adaptive filtering example: histogram equalization (HE)

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

where hist: local histogram

- $r$: quantized ranges

- local contrast enhancement

- local + global distribution information

Zhu et al. CVIA (73), 1999

(global dynamic range) global HE local HE (adapthisteq) to be replaced with overlapping LHE
Locally adaptive filtering example: bilateral filter (BF)

\[ p_{\mathcal{N}}(x) = \sigma_r(x) \]

\[ k_s(x, x') = e^{-\frac{||x-x'||^2}{\sigma_s^2}} \]

\[ k_r(I(x), I(x')) = e^{-\frac{||I(x)-I(x')||^2}{\sigma_r^2(x)}} \]

(space- and range-kernels)

- boundary-preserving denoising
- local adaptation to boundary “jumps”

Tomasi & Manduchi. ICCV, 1998
Locally adaptive filtering example: bilateral filter (BF)

\[ p_{\mathcal{N}}(x) = \sigma_r(x) \]
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\[ k_r(I(x), I(x')) = e^{-\frac{||I(x)-I(x')||^2}{\sigma_r^2(x)}} \]

(space- and range-kernels)

- boundary-preserving denoising
- local adaptation to boundary “jumps”

\( \sigma_s = 1.5, \sigma_r = 0.157 \) (residual image)

Tomasi & Manduchi. ICCV, 1998
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)
Locally adaptive filtering: analytic advance & technical challenges

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- Challenge traditional parallel primitives in multiple aspects
  (algorithmic complexity, concurrency, numerical behavior)
Locally adaptive filtering: analytic advance & technical challenges

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- Permit spatially inhomogeneous noise behavior
  (often observed in medical imaging)
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  (including histograms and some bilateral filters)
- Challenge traditional parallel primitives in multiple aspects
  (algorithmic complexity, concurrency, numerical behavior)
- 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**

```
locStat = localStat = local

\[
\begin{align*}
\text{Mean} & \quad (\text{Image, b}) \\
\text{Std} & \quad \text{Tile}(\text{Image, b, t}) \\
\text{Min} & \quad \text{Tile1x1}(\text{Image, b}) \\
\text{Max} & \\
\text{Median} & \\
\text{Mad} & \\
\text{Hist} & \\
\text{Entropy} &
\end{align*}
\]
```

```
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

Integral : 2
Integral $x^2 : 3$
Mean : 4
$\sum x^2 : 3$
StD : 3
Median : 14w
MAD : 14w
Min Max : 3
Integral Histogram : 2b
Local Histogram : 3b
Entropy : 2b

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

\[(D + 1)\text{-dimensional grid embedding, with local dynamic range bins}\]

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 targets

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

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

global and ROI-specific 32-bin Shannon distributions
Local statistics exploration

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

example 32-bin local histograms

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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
Local statistics exploration

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 ($\theta = 21^\circ$)

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™ 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

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Single precision error in Mean and STD for 1000x1000 image

![Graph showing error vs. tile size](image)

Histogram difference for same ROI

![Histogram showing frequency](image)
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

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### Timing Results

#### localStats Kernel over image size

<table>
<thead>
<tr>
<th>Image Size</th>
<th>Time (msec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>5</td>
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<tr>
<td>1000</td>
<td>10</td>
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<tr>
<td>1500</td>
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<tr>
<td>2500</td>
<td>25</td>
</tr>
<tr>
<td>3000</td>
<td>30</td>
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</tbody>
</table>

- $T = 20 \times 20$ localStat
- $T = 20 \times 20$ MATLAB

#### localStats Kernel over image size

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<tr>
<td>3000</td>
<td>30</td>
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</tbody>
</table>

- $T = 30 \times 30$ localStat
- $T = 30 \times 30$ MATLAB

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Timing Results

Timing ratio between whole image and tile for `localStats`

![Graph showing timing ratio between whole image and tile for `localStats` with data points for different image sizes and tile sizes.]

Timing ratio between whole image and tile for `localStats`

![Graph showing timing ratio between whole image and tile for `localStats` with data points for different image sizes and tile sizes.]

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Timing Results

Multiple kernels all timings

Timing for histogram prefix sum

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References


