Integrated Imaging: Creating Images from the Tight Integration of Algorithms, Computation, and Sensors

Charles A. Bouman
School of Electrical and Computer Engineering
Purdue University
Electronic Imaging Symposium
2014-02-04

Co-authored with:
- Ken Sauer, University of Notre Dame
- Jean-Baptiste Thibault, GE Healthcare
- Jiang Hsieh, GE Healthcare
- Zhou Yu, GE Healthcare
- Venkat Venkatakrishnan, Purdue
- Larry Drummy, AFRL
- Marc De Graef, CMU
- Jeff Simmons, AFRL
- Brendt Wohlberg, LANL
- Peter Voorhees, Northwestern University
- Greg Buzzard, Purdue University

• Supported by:
  • GE Healthcare
  • Air Force Office of Scientific Research, MURI contract # FA9550-12-1-0458, and the Air Force Research Laboratory
  • Department of Homeland Security ALERT Center of Excellence, Northeaster University
Integrated Imaging: Combining Algorithms and Physical Sensors

- Traditional sensor design is reaching its limits
  - Difficult to only measure one parameter
  - No longer possible to “fix” the device

- Rather than making the “purest” measurement, make the most informative measurement.

- Requires tight integration of sensor and algorithms.
Integrated Imaging: The Philosophy

- Mick Jagger’s Theorem: You can’t always get what you want, but if you try sometimes, you might get what you need.
  - What should you get (measure)?
  - How do you form an image from what you get?

- What should you get (measure)?
  - Don’t measure one thing at a time very precisely
  - Measure everything mixed together adaptively

- Forming an image from data
  - Use all available information to form the image
  - Combine measurements and prior knowledge

*Disclaimer: My talk will only touch on a fraction of what is out there.*
Inverse Problem: Example

- Forward model
  - Gravity
  - Fluid dynamics
  - Light propagation
  - Image formation

- Inversion
  - Illumination estimation
  - Shape from X
  - Inverse dynamics
  - Real world knowledge

- Inverse Solution: Something fell in the water
Model Based Iterative Reconstruction (MBIR): A General Framework for Solving Inverse Problems

\[ \hat{x} \leftarrow \arg \max_x \left\{ \log p(y \mid x) + \log p(x) \right\} \]

- \( \hat{x} \) – Reconstructed object
- \( y \) – Measurements from physical system
- \( x \) – Physical system
“Thin Manifold” View of Prior Models

- Notice that prior manifold fills the space but...
  - Not a linear manifold
  - PCA can not effectively reduce dimension
- But it has thickness
- Dimension of measurement > dimension of manifold
Recipe for Integrated Imaging

- Design sensor to measure the most informative data

- Form image:
  - Solve inverse problem: Data in => image out
  - Synergy between forward model of sensor and prior model of image

- Explosion of possibilities:
  - Mix and match sensors and models
  - Do things you couldn’t do before
Medical CT Imaging
Ken Sauer, University of Notre Dame
Jean-Baptiste Thibault, GE Healthcare
Jiang Hsieh, GE Healthcare
Multi-slice Helical Scan Medical CT

- Reconstruct 3D volume from 1D projections
- Geometry:
  - Helical scan
  - Multislice => cone angle in 3D
Model-Based Iterative Reconstruction (MBIR)

Fwd Model $f(x) = Ax$

Error Sinogram $(Ax - y)$

$$\hat{x} = \arg \min_{x \geq 0} \left\{ -\log p(y \mid x) - \log p(x) \right\}$$

$$= \arg \min_{x \geq 0} \left\{ \frac{1}{2} \left\| y - Ax \right\|_{\Lambda}^2 + u(x) \right\}$$
CT Scanner Forward Model: \( p(y|x) \)

- Measure X-ray attenuation
  \[ y_i = -\ln \left( \frac{\lambda_i}{\lambda_T} \right) \]

- Assumptions
  \[ E[y|x] = Ax \]
  \[ Var[y|x] = \Lambda \]

**Important!** \( Var[y_i|x] = \Lambda_{i,i} = \frac{\lambda_i + \sigma_e^2}{\lambda_i^2} \) – Photon counting + electronic noise

Forward model:
\[ -\log p(y|x) = \frac{1}{2} \| y - Ax \|^2_{\Lambda} + \text{constant} \]
Markov Random Field (MRF) Prior Model

- Gibbs Distribution
  \[ p(x) = \frac{1}{Z} \exp \left\{ - \sum_{\{j,k\} \in C} \rho \left( \frac{x_j - x_k}{\sigma} \right) \right\} \]

  \( \rho \left( x_j - x_k \right) \): Potential function

- Properties:
  - MRF with 26 local neighbors in 3D
  - \( \rho(\Delta) \) preserves edges

Prior model:

\[- \log p(y \mid x) = - \sum_{\{j,k\} \in C} \rho \left( \frac{x_j - x_k}{\sigma} \right)\]
Choice of MRF Potential Function

$\rho(f_i - f_j)$: Penalty on the difference between neighboring voxels

If $\rho(f_i - f_j) = \frac{|f_i - f_j|^2}{\sigma_f}$

$q$-Generalized Gaussian MRF*

$p = 2$ corresponds to diffuse interfaces

$p = 1$ corresponds to sharp interfaces
- Total Variation Regularization
  (compressed sensing)

$\sigma_f$: MRF scaling parameter (controls noise)

Optimization for MAP Estimation

\[ \hat{x} = \arg\min_{x \geq 0} \left\{ \frac{1}{2} (y - Ax)^T \Lambda (y - Ax) + u(x) \right\} \]

- **Approaches**
  - ICD – fast robust convergence, but not so GPU friendly
  - Gradient based optimization – GPU friendly, but more fragile

- **Other important tricks:**
  - Non-homogeneous updates
  - Preconditioning
  - Ordered subsets
  - Nested optimization
  - Multiresolution/Targetting
RMSE Convergence Plots for NH-ICD

- NH-ICD
  - Reduces transients at early stage allowing faster convergence
  - Interleaving in early iterations further improves convergence speed

Model-Based Iterative Reconstruction (MBIR): GE Healthcare’s Veo System

• What is Veo?
  – GE announce new product, “Veo”, based on MBIR reconstruction at RSNA 2010
  – System received FDA 510(k) approval in 2011
  – Currently on sale in US as an upgrade option
  – Partnership between GE Healthcare, Purdue University and the University of Notre Dame
  – Research team:
    • Jean-Baptist Thibault, Jiang Hsieh (GE)
    • Ken Sauer (Notre Dame)
    • Me (Purdue)
Resolution vs Noise

GEPP wire, 16x0.625mm, P15/16:1, 100mA, 10cm fov

MTF comparable to FBP bone
50% lower noise than FBP std
Challenges usual trade-off

<table>
<thead>
<tr>
<th></th>
<th>IQ</th>
<th>FBP std</th>
<th>FBP bone</th>
<th>MAP-ICD</th>
</tr>
</thead>
<tbody>
<tr>
<td>50% MTF</td>
<td>4.39</td>
<td>8.53</td>
<td>8.66</td>
<td></td>
</tr>
<tr>
<td>10% MTF</td>
<td>7.04</td>
<td>11.90</td>
<td>13.20</td>
<td></td>
</tr>
<tr>
<td>Std dev</td>
<td>24.99</td>
<td>90.94</td>
<td>13.01</td>
<td></td>
</tr>
</tbody>
</table>
MBIR for 64 slice GE VCT Data

State-of-the-art 3D Recon

GE MBIR
Purdue/Notre Dame/GE algorithm
MBIR for 64 slice GE VCT Data

State-of-the-art 3D Recon
Purdue/Notre Dame/GE algorithm
MBIR for 64 slice GE VCT Data

State-of-the-art 3D Recon

Purdue/Notre Dame/GE algorithm
Pediatric Image at Low Dose (Coronal)

Free fluid/Blood in abdomen seen more clearly
Bladder better visualized
Liver laceration better defined

ASiR Reconstruction

MBIR Reconstruction

Pediatric trauma, 120kV, 52-70mA, 0.4s/rot, 0.625mm, WW 300 WL 50

Images courtesy of The Queen Silvia Children’s Hospital
Dr. Stålhammar
Pediatric Image at Low Dose (Transverse)

ASiR Reconstruction

MBIR Reconstruction

Images courtesy of The Queen Silvia Children’s Hospital
Dr. Stålhammar

Pediatric trauma, 120kV, 52-70mA, 0.4s/rot, 0.625mm, WW 300 WL 50
Abdomen Imaging

Adrenal nodule

FBP Reconstruction  MBIR Reconstruction

kV 120, mA 150, 0.5s, 0.625mm, WW 350 WL 50 DFOV 42 Standard kernel in FBP

Images courtesy of Dr Gladys Lo
Time Interlaced Model Based Iterative Reconstruction (TIMBIR)

K. Aditya Mohan, Purdue
John Gibbs, NW
Prof. Peter Voorhees, NW
Prof. Marc De Graef, CMU
Dr. Xianghui Xiao, APS
Prof. Charles Bouman, Purdue
Synchrotron Imaging

Why are they important?
- Intense, columnated, monochromatic source of X-rays
- Have become more widely available

Facilities
- Advanced Photon Source (APS), Argonne National Labs; Advance Light Source (ALS), Lawrence Berkeley Labs; Cornell High Energy Synchrotron Source (CHESS); Stanford Synchrotron Radiation lightsource (SLAC); National Synchrotron Light Source, Brookhaven; Swiss Light Source.
Synchrotron Imaging of Time-Varying Sample

Real Synchrotron Projection Data

2-D cross section

Temporal evolution of the sample
Conventional Approach to 4D Synchrotron Imaging

- Traditional approach
  - Acquire $N_v=2000$ views; do FBP reconstruction; repeat
  - Reduces time resolution by $N_v=2000$ !!

- How do we increase temporal resolution ?
**TIMBIR: Time Interlaced Model Based Iterative Reconstruction**

- Interlace the views over $K$ rotations of the object.

- Perform 4D MBIR reconstruction at any desired temporal resolution.

Projections

Reconstructions
Examples of Interlaced Views

- Total number of discrete angles used is a constant.

- The time taken for rotation of object by 180 degrees decreases as K increases (or L decreases).
Number of Reconstructions per Frame, $r$

**Case 1**

$r = 1$

1 reconstruction for every 16 projections.

**Case 2**

$r = 2$

1 reconstruction for every 8 projections.
3D Reconstructions – FBP vs. TIMBIR

<table>
<thead>
<tr>
<th></th>
<th>Phantom</th>
<th>MBIR/No Interlace</th>
<th>TIMBIR</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Phantom</td>
<td>MBIR/No Interlace</td>
<td>TIMBIR</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>Phantom</td>
<td>MBIR/No Interlace</td>
<td>TIMBIR</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>Phantom</td>
<td>MBIR/No Interlace</td>
<td>TIMBIR</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>A</th>
<th>Phantom</th>
<th>RMSE (HU)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>MBIR/No Interlace</td>
<td>2586.8</td>
</tr>
<tr>
<td></td>
<td>r = 1, K = 1, N_θ = 256</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>TIMBIR</td>
<td>1773.1</td>
</tr>
<tr>
<td></td>
<td>r = 16, K = 16, N_θ = 256</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>FBP/No Interlace</td>
<td>5451.5</td>
</tr>
<tr>
<td></td>
<td>r = 1, K = 1, N_θ = 256</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>FBP/Interlace</td>
<td>11258</td>
</tr>
<tr>
<td></td>
<td>r = 16, K = 16, N_θ = 256</td>
<td></td>
</tr>
</tbody>
</table>
TIMBIR vs. FBP - Y Axis Slice

Phantom

MBIR/No Interlace

TIMBIR

FBP/No Interlace

FBP/Interlace

$N_\theta = 256$
# TIMBIR: Synergy Between View Sampling and MBIR Reconstruction

- TIMBIR results in synergistic improvement

<table>
<thead>
<tr>
<th></th>
<th>FBP</th>
<th>MBIR</th>
</tr>
</thead>
</table>
| Conventional View Sampling | • Low noise robustness  
• Low temporal resolution  
• Medium quality        | • High noise robustness  
• Low temporal resolution  
• High quality           |
| Interlaced View Sampling  | • Low noise robustness  
• High temporal resolution  
• Low quality            | • High noise robustness  
• High temporal resolution  
• High quality           |

**TIMBER**
Validation using Real Data

- **Facilities**
  - Advanced Photon Source (APS) synchrotron at Argonne National Laboratory
  - High performance computer at Advanced Light Source (ALS) at Lawrence Berkeley Laboratory

- **Objectives**
  - To reconstruct the solidification of Al-Cu microstructures at high temporal resolution.
  - Evaluate TIBIR method.
TIMBIR with $K = 16$

**Experiment**
- Solidification of aluminum and copper mixture
- Temperature decreased at 2$^\circ$ Celsius per minute
- $k=16$; $r=16$; $N_v=2000$
- 16x speed up

**Reconstruction**
- (2048 x 2048 x 1000) space x 16 time
- $(0.65 \mu m)^3$ voxel size
- 1.8 sec time step
- Image scaling: 10000 HU to 60000 HU
4D Segmentation of TIMBIR with $K = 16$
Electron Microscopy (EM)
Microscopy for Material Science
Venkat Venkatakrishnan, Purdue
Larry Drummy, AFRL
Marc De Graef, CMU
Jeff Simmons, AFRL
Electron Microscopy (EM) Imaging

- 2-D Characterization of samples (biology, material science)
- Various modalities (Bright Field, Dark Field etc.)

* [http://bio3d.colorado.edu/Imod/doc/etomoTutorial.html](http://bio3d.colorado.edu/Imod/doc/etomoTutorial.html)

** L.F. Drummy, AFRL
Bright Field (BF) vs. Dark Field Imaging

Bright Field:
Image is bright when sample is removed

Dark Field:
Image is dark when sample is removed
The Problem with Bright Field EM

- Crystalline materials create Bragg scatter
- When Bragg scatter occurs, particle is dark => Beers Law is wrong!

\[ \int \mu(r) \, dr \neq -\log \left( \frac{\lambda_j}{\lambda_0} \right) \]

- “Tomography doesn’t work”
MBIR Reconstruction with Bragg Rejection

\[
(f, d) = \arg \min_{f \geq 0, d} \left\{ \frac{1}{2} \sum_{i=1}^{M} \beta_{T, \delta} \left( (g_i - A_{i*}f - d) \sqrt{\Lambda_{ii}} \right) + \sum_{\{i,j\} \in \chi} w_{ij} \rho(f_i - f_j) \right\}
\]

**Forward Model With Bragg Rejection**

\(f\): Linear attenuation coefficients to reconstruct (\(\text{nm}^{-1}\))

\(g_i = -\log(\lambda_i)\)

\(d = -\log(\lambda_D)\)

\(\lambda_i\): Measured BF signal (counts)

\(\lambda_D\): Unknown Dosage (counts) - can be estimated

\(\beta_{T, \delta}(e) = \begin{cases} e^2 & |x| \leq T \\ 2T \delta |x| + T^2 (1 - 2\delta) & |x| > T \end{cases}\)

\(\Lambda_{ii}\): \(\frac{1}{\text{Noise variance}}\) (scaled) for measurement \(i\)

\(A_{i*}\): \(i^{th}\) row of forward projection matrix

\(M\): Total number of measurements

**Eliminate the effect of Bragg anomalies**
Generalized Huber Function

- Reduce effect of outliers due to Bragg

- Generalized Huber Function
  - Proper distribution $\Rightarrow$ ML estimation of threshold $T$
  - Surrogate function (majorization) for optimization

\[
\beta_{T,\delta}(e) = \begin{cases} 
  e^2 & |x| \leq T \\
  2T \delta |e| + T^2 (1 - 2\delta) & |x| > T
\end{cases}
\]

$e \rightarrow$ Measurement error

$\beta_{T,\delta} \rightarrow$ Generalized Huber function
**Al –TEM Data (Movie)**

Reconstruction params
Region : $Y - [920, 974]$
$X - [563, 1484]$
Thickness = 350 nm
$p = 1.2$
$\sigma_f = 1.6 \times 10^{-4} \text{ nm}^{-1}$
Recon Voxels = $(2 \times 0.83)^3 \text{ nm}^3$
$T = 3; \delta = 0.5$

Average value in a void region

Data range (int) : $[-32728, -21780]$
Preprocess to (uint) : $[40, 10988]$
Reconstruction: x-z cross section

- FBP*
- MBIR – No anomaly correction
- MBIR – with anomaly correction

\[ \sigma_f = 1.6 \times 10^{-4} \text{nm}^{-1} \]
Reconstruction: x-y cross section

FBP*

MBIR – No anomaly correction

MBIR – with anomaly correction
Bragg Anomaly Classification

- MBIR-BF cost function labels Bragg
- Identify Bragg signature of particles
- Requires 3D segmentation

\[ \hat{\sigma}^2 = 3.03 \]
Fraction classified: 3.92%
“Bragg Feature Vector” Extraction Algorithm

BF Tilt Series Data (Movie)

MBIR → 3D Reconstruction → Particle Segmentation → Particle Projections

Correlation & Threshold → Anomaly Classifier → Projected Particle

Bragg feature vector for particle
Extracted Bragg Feature Vectors

MBIR Reconstruction  Segmented Particles

Bragg Feature Vector for Each Particle
Advanced Priors Models
S. Venkat Venkatakrishnan, Purdue University
Brendt Wohlberg, Los Alamos National Laboratory
Suhas Sreehari, Purdue University
Garth J Simpson, Purdue University
Charles A. Bouman, Purdue University
Prior Modeling of Images

- An open problem of great importance
  - Low, mid, high level models
  - Crucial in denoising problems

- Promising recent approaches:
  - MRFs; Dictionary bases learning methods; kSVD; Non-local means; BM3D; Bilateral filters; Gaussian mixture models (GMMs)

- Many of these are not really prior models
Plug & Play Priors Algorithm

- Can use “any” denoising model as a “prior”
Deblurring with Many “Priors”

Ground Truth  Blurred, Noisy Data  K-SVD  BM3D

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground Truth</td>
<td>13.13</td>
</tr>
<tr>
<td>Blurred, Noisy Data</td>
<td>13.91</td>
</tr>
<tr>
<td>K-SVD</td>
<td>14.95</td>
</tr>
<tr>
<td>BM3D</td>
<td>15.21</td>
</tr>
<tr>
<td>PLOW</td>
<td>14.14</td>
</tr>
<tr>
<td>TV</td>
<td>15.21</td>
</tr>
<tr>
<td>q-GGMRF</td>
<td>14.14</td>
</tr>
</tbody>
</table>
Inpainting with Many “Priors”

Ground Truth  Subsampled Image  K-SVD  BM3D

Noise std. dev : 5% of max signal  RMSE : 14.11  RMSE : 12.56

PLOW  TV  q-GGMRF

RMSE : 14.54  RMSE : 15.50  RMSE : 15.72
Scan dynamic sample in space and time
Model Based Dynamic Sampling (MBDS)

- Dilshan P. Godaliyadda, Purdue University
- Prof. Gregery T. Buzzard, Purdue University
- Prof. Charles A. Bouman, Purdue University
Raster Sampling: Optimally Bad

- Each new sample provides the least information.
Random Sampling: Better

- Each new sample provides much more information.
Optimal (Greedy) Sampling: Best

- Each new sample provides the most information.
Recursion for Optimal Greedy Sampling

For each new sample {

\[ y^{(k)} = A^{(k)} x + w^{(k)} \]

Step 1: Measure signal

\[ \mu_{x|y^{(k)}} = \mathbb{E}[x|y^{(k)}] \]

\[ R_{x|y^{(k)}}^{(k)} = \mathbb{E}[(x - \mu_{x|y^{(k)}})(x - \mu_{x|y^{(k)}})^T | y^{(k)}] \]

When everything is Gaussian, \( R_{x|y}^{(k)} \) does not depend on \( y^{(k)} \)!!!!

\[ m^{(k)} \leftarrow \arg \max_{m \in M} \left( m^T R_{x|y}^{(k)} m \right) \]

Step 2: Find posterior covariance of image

Step 3: Select pixel with largest variance

\[ A^{(k+1)} = \begin{pmatrix} A^{(k)} \\ m^{(k)} \end{pmatrix} \]

Step 4: Add new row to \( A \) matrix

}\}
Non-Gaussian Prior $\Rightarrow$ Dynamic Sampling

- Likely location of solution
- Best measurement direction
- $x_1$ prior manifold
- $x_2$
Non-Gaussian Prior $\Rightarrow$ Dynamic Sampling

- Optimal sampling depends dynamically on previous samples

- Non-Gaussian $\Rightarrow$ Intractable calculation of posterior 😞
Solution: Hastings-Metropolis Sampling of Posterior

For each new sample \{ 

\begin{align*}
  y^{(k)} &= A^{(k)} x + w^{(k)} \\
  \{x^{(1)}, x^{(2)}, \ldots, x^{(L)}\} &\sim p(x \mid y^{(k)})
\end{align*}

\begin{align*}
  \hat{\mu}_n &\leftarrow \frac{1}{L} \sum_{i=1}^{n} x^{(i)}_n \\
  \hat{\sigma}_n^2 &\leftarrow \frac{1}{L-1} \sum_{i=1}^{L} (x^{(i)}_n - \hat{\mu}_n)^T (x^{(i)}_n - \hat{\mu}_n)
\end{align*}

\begin{align*}
  n^{(k)} &= \arg\max_n \left( \hat{\sigma}_n^2 \right)
\end{align*}

\begin{align*}
  A^{(k+1)} &= \begin{pmatrix}
    A^{(k)} \\
    0, \ldots, 1, \ldots, 0
  \end{pmatrix}
\end{align*}

\}

\textbf{Step 1: Measure signal}

\textbf{Step 2: Generate L samples from posterior}

\textbf{Step 3: Estimate posterior variance}

\textbf{Step 4: Select pixel with largest variance}

\textbf{Step 5: Add new row to A matrix}
Dynamic Sampling of 1D Signal

How to do this computation tractably in 2D?
2D Hastings-Metropolis Sampler

- Select pixel with largest sample variance

L = 20 images generated from posterior

- Replace window of pixels using Hastings-Metropolis
Dynamic Sampling for Phantom

Selected Samples

MAP Reconstructed Image
Dynamic Sampling for SEM Image

Tony Fast, Georgia Tech

Selected Samples

MAP Reconstructed Image
Analogy to Human Visual System

- Visual scanpath theory and saccadic movement of eye – *Stark, Privitera, Navalpakkam*
  - Bottom up => sensor model
  - Top down => prior model

- Interesting observations: Each pixel is selected to maximize information without knowledge of local edge structure.
Major directions for Integrated Imaging

- Creative design of sensor systems

- Image formation:
  - Forward modeling: Account for complex nonlinear parameters and models
  - Prior modeling: Account for properties of real images

- Community: Create interdisciplinary teams to solve high impact problems