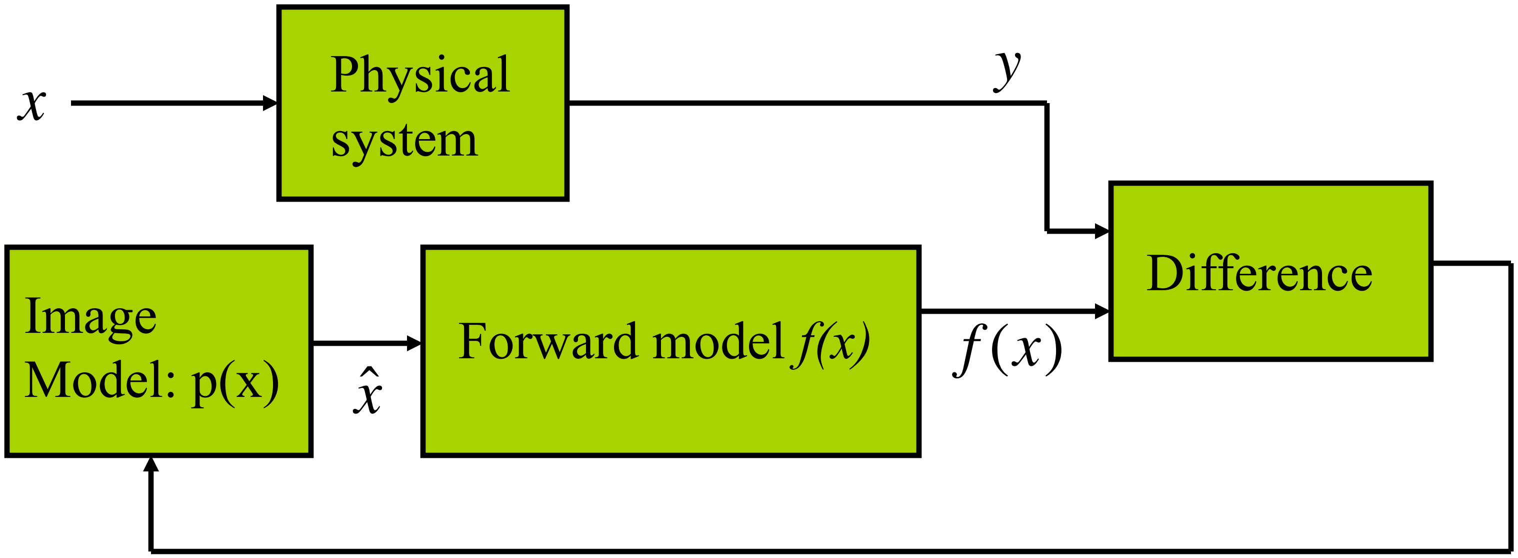
Current Thoughts on Tomography Tools-Input Comments Sought

Charles A. Bouman
School of Electrical and Computer Engineering
Purdue University

Presentation to Air Force Research Laboratory (AFRL)
April 8, 2011

Model-Based Iterative Reconstruction



$\hat{x}$ – Reconstructed image

y – Measurements from physical system

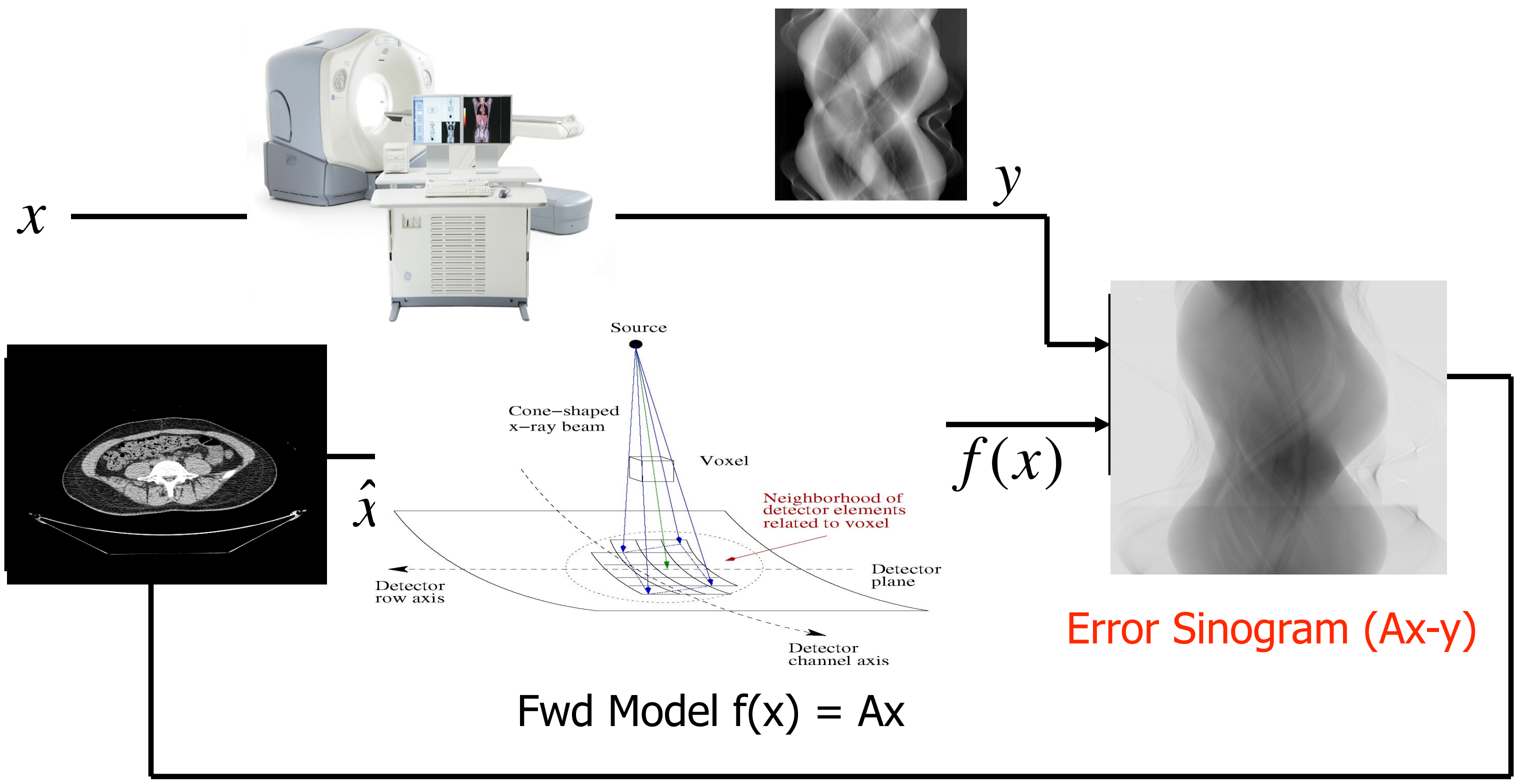
$$\hat{x} = \arg\min_x \left\{ \|y - f(x)\|_\Lambda^2 + U(x) \right\}$$

- Bayesian framework

$$U(x) = -\log p(x)$$ *- prior model*

$$\|y - f(x)\|_\Lambda^2 = -\log p(y \mid x)$$ *- forward model*

Example: Multislice Helical CT



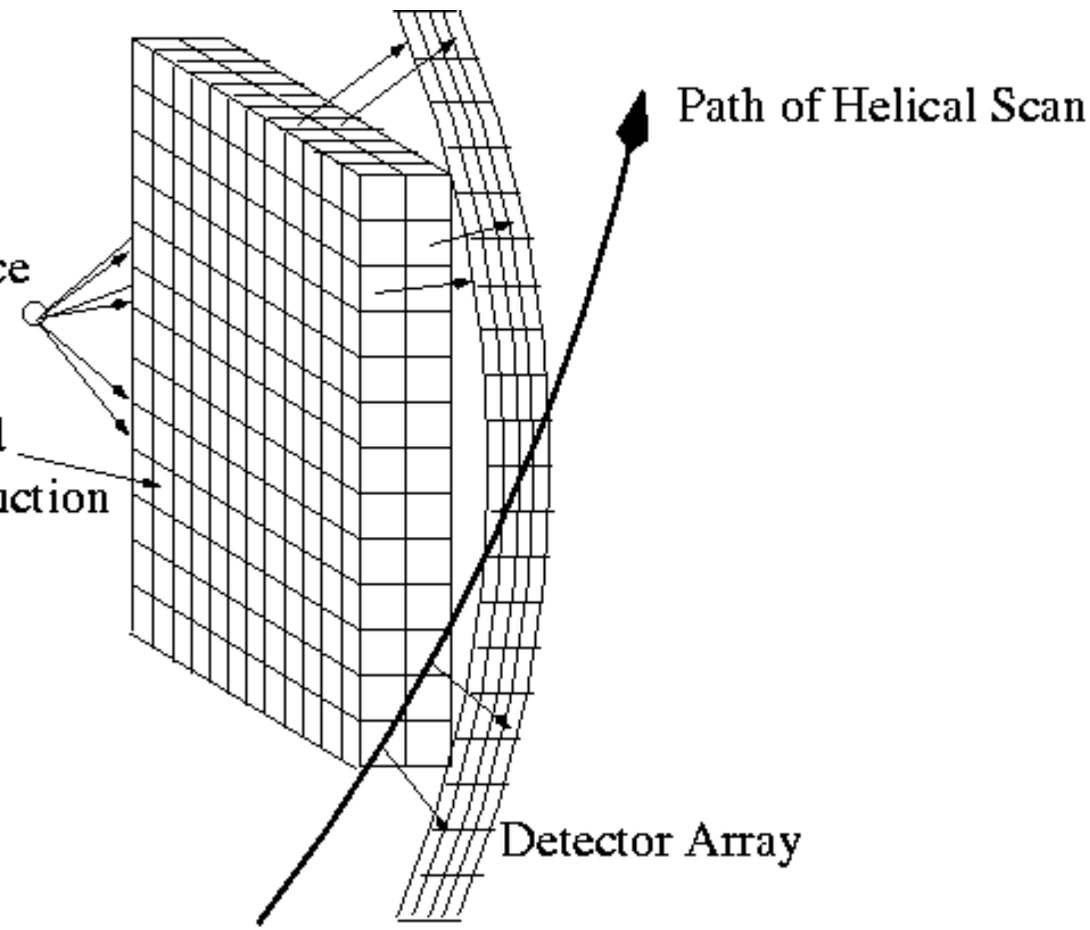
Cost Function

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

- D: statistical weighting
- U(x): image regularization

Scanner Forward Model

Physical system



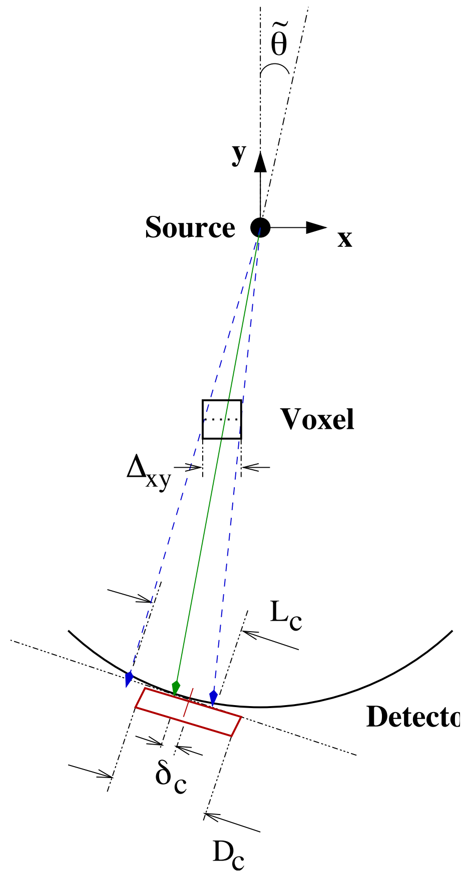
λ_i : The photon count

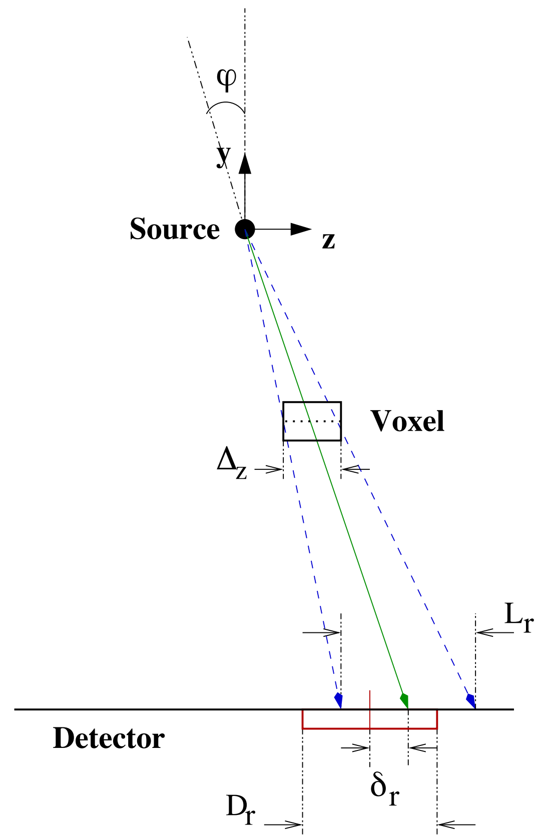
λ_T : The dosage

$$y_i = \ln\left(\frac{\lambda_T}{\lambda_i}\right)$$: line integral of the attenuation coefficients

Distance Driven Projector*

- Fast and accurate projection of 3D voxels





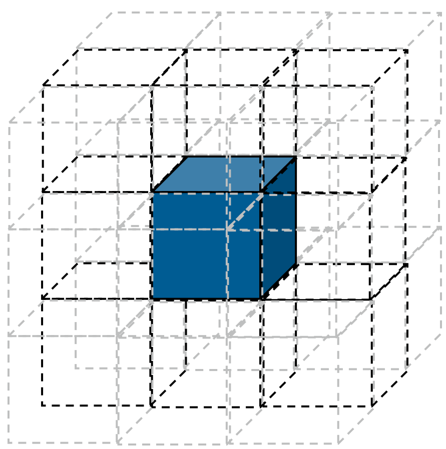
B. DeMan and S. Basu, “Distance-driven projection and backprojection in three-dimensions,” Physics in Medicine and Biology, vol. 49, pp. 2463–2475, 2004.

Jean-Baptiste Thibault, Ken Sauer, Charles Bouman, and Jiang Hsieh, “A Three-Dimensional Statistical Approach to Improved Image Quality for Multi-Slice Helical CT,” *Medical Physics*, pp. 4526-4544, vol. 34, no. 11, November 2007.

Image Prior Model

Image x

Model: $p(x)$



$$U(\mathbf{x}) = \frac{1}{p\sigma^p} \sum_{\{j,k\} \in C} \rho(x_j - x_k)$$

$\rho(\Delta) = \lvert\Delta\rvert$	"Compressed sensing"
$\rho(\Delta) = \lvert\Delta\rvert^p$ where $p = 1.2$	Generalized Gaussian MRF
$\rho(\Delta) = \dfrac{\lvert\Delta\rvert^q}{1 + \lvert\Delta / 50\rvert^{q-p}}$ with $p = 1.2$ and $q = 2$	Q-GGMRF

- 3D regularization using 26 neighbors
- Design to:
  - Preserve high contrast edges
  - Enhance low contrast sensitivity
- Q-GGMRF
  - Convex for $1 \leq q \leq p \leq 2$
  - Behaves like x^p for $|x|$ small
  - Behaves like x^q for $|x|$ large

Jean-Baptiste Thibault, Ken Sauer, Charles Bouman, and Jiang Hsieh, "A Three-Dimensional Statistical Approach to Improved Image Quality for Multi-Slice Helical CT," *Medical Physics*, pp. 4526-4544, vol. 34, no. 11, November 2007.

Model-Based Image Reconstruction

Charles A. Bouman, Professor of ECE Purdue University

- Multislice helical scan computed tomgraphic (CT) imaging
  - Estimated 72 million CT scans in the US in 2007.
  - Dramatic increase has virtually eliminated the need for “exploratory surgery”.
  - Since inception, commercial scanners have used filtered back projection (FBP).
  - Cumulative X-ray dosage from CT of growing concern.
- Model-Based Iterative Reconstruction (MBIR)
  - Compute the “best” reconstruction given the data and known statistics of images.
  - Uses iterative process to fit reconstruction to measurements.
- GE Healthcare Veo product - *“I see” in Spanish*
  - GE Healthcare’s commercial software/hardware implementation of MBIR
  - On sale in Europe - http://radiologynews.gehealthcare.com/en/computed/pm/detail/0/200/4/veo-.html
  - Pending FDA 510(k) review for use in the US.
  - Dosage reduction of ~4x
  - Research performed in collaboration with:

    Ken Sauer, University of Notre Dame

    Jean-Baptiste Thibault, GE Healthcare

    Jiang Hsieh, GE Healthcare

MBIR/Veo Publications and Patents

- Some key publications:

  K. Sauer and C. Bouman, "A Local Update Strategy for Iterative Reconstruction from Projections," *IEEE Trans. on Sig. Proc.*, vol. 41, no. 2, pp. 534-548, Feb. 1993.

  C. A. Bouman and K. Sauer, "A Unified Approach to Statistical Tomography using Coordinate Descent Optimization," *IEEE Trans. on Image Processing*, vol. 5, no. 3, pp. 480-492, March 1996.

  J.-B. Thibault, K. Sauer, C. Bouman, and J. Hsieh, "A Three-Dimensional Statistical Approach to Improved Image Quality for Multi-Slice Helical CT," *Medical Physics,* pp. 4526-4544, vol. 34, no. 11, November 2007.

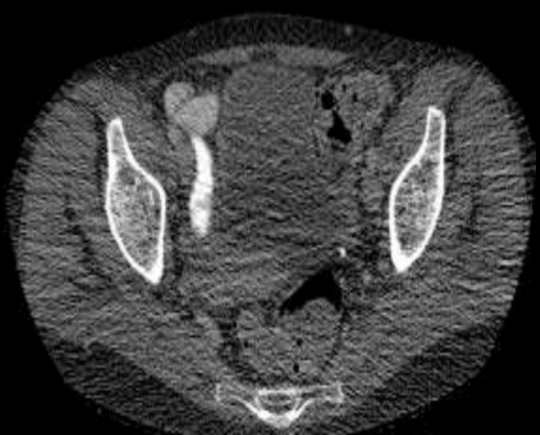
- Issued patents:

  1. J. Hsieh, J.-B. Thibault, C. A. Bouman, and K. Sauer, "An Iterative Method for Region-of-Interest Reconstruction," US Pat. 6,768,782, July 27, 2004.
  2. 9. K. Sauer, C. A. Bouman, J.-B. Thibault, and J. Hsieh, "Iterative Reconstruction Methods for Multi-Slice CT," US Pat. 6,907,102, June 14, 2005.
  3. K. D. Sauer, J.-B. Thibault, C. A. Bouman, and J. Hsieh, "Methods, Apparatus, and Software to Facilitate Iterative Reconstruction of Images," US Pat. 7,251,306, July 31, 2007.
  4. J.-B. Thibault, K. D. Sauer, C. A. Bouman, and J. Hsieh, "Methods, Apparatus, and Software to Facilitate Computing the Elements of a Forward Projection Matrix," US Pat. 7,272,205, Sep. 18, 2007.
  5. C. A. Bouman, K. D. Sauer, J. Hsieh, and J.-B. Thibault, "Methods, Apparatus, and Software for Reconstructing an Image," US Pat. 7,308,071, Dec. 11, 2007.
  6. K. D. Sauer, J.-B. Thibault, C. A. Bouman, and J. Hsieh, "Method, Apparatus, and Software for Reconstructing an Image," US Pat. 7,327,822, Feb. 5, 2008.
  7. J. Hsieh, C. A. Bouman, K. D. Sauer, and J.-B. Thibault, "Methods, Apparatus, and Software for Failed or Degraded Components," US Pat. 7,440,602, Oct. 21, 2008.
  8. J. Hsieh, J.-B. Thibault, K. D. Sauer, and C. A. Bouman, "Method and System for Improving a Resolution of an Image," US Pat. 7,583,780, Sept. 1, 2009.
  9. K. D. Sauer, C. A. Bouman, J. Hsieh, and J.-B. Thibault, "Systems and Methods for Filtering Data in Medical Imaging Systems," US Pat. 7,676,074, Mar. 9, 2010.
  10. K. D. Sauer, C. A. Bouman, J. Hsieh, and J.-B. Thibault, "Method and System for Image Reconstruction," US Pat. 7,885,371, Feb. 8, 2011.

Routine abdomen pelvis
Dose - 0.77 mSv*

DLP 45, 0.625 mm
100 kVp, 37–51 mA,

MBIR/Veo



FBP

FBP Reconstruction

MBIR/Veo Reconstruction

High resolution with low noise

FBP Reconstruction

MBIR/Veo Reconstruction

Standard algorithm

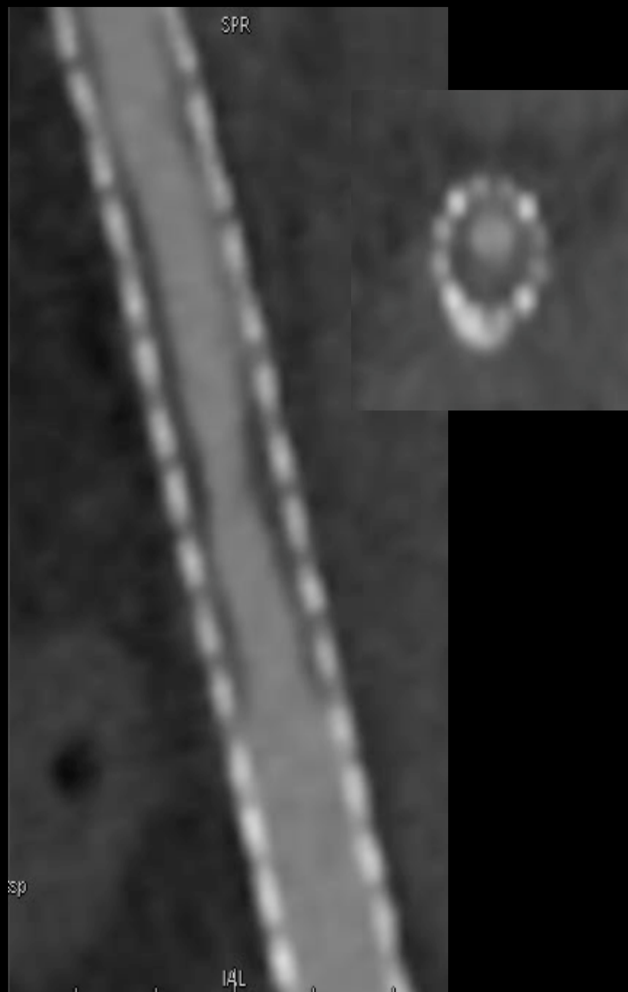
WW 350 WL 50

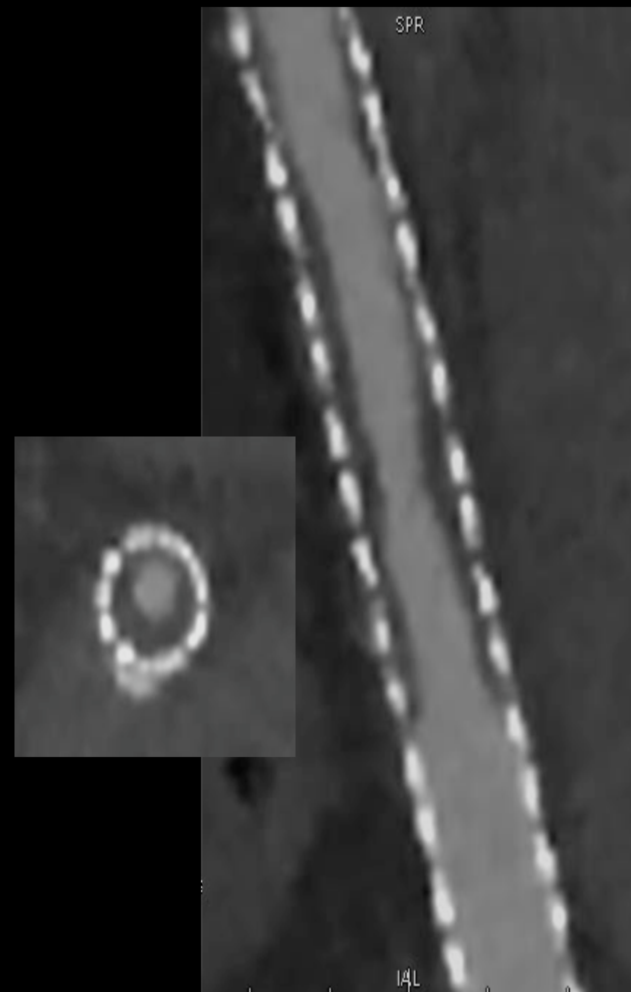
Bone Plus algorithm

WW 2000 WL 400

Improving resolution & contrast

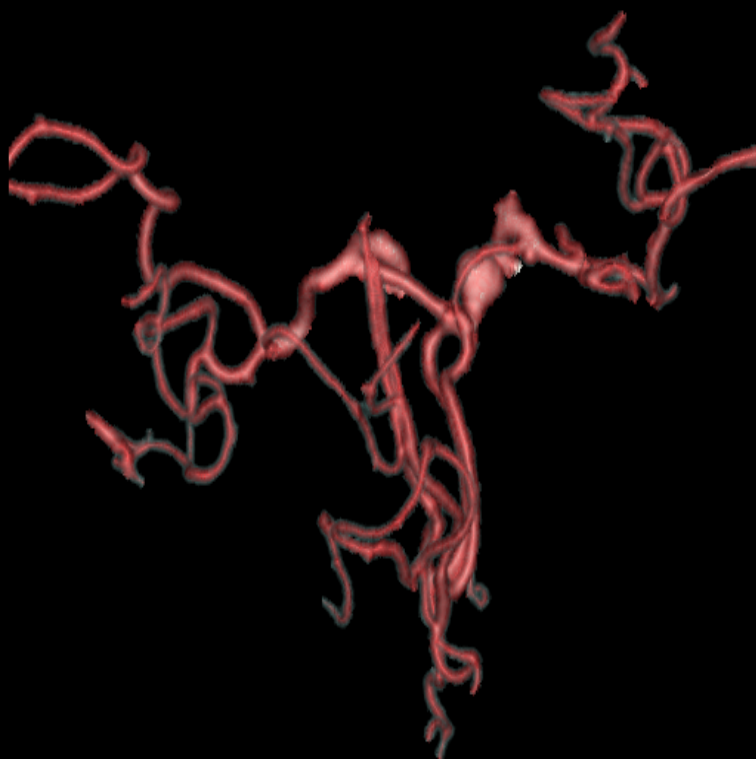
FBP





MBIR/Veo

Improved detail



FBP Reconstruction

MBIR/Veo Reconstruction

Routine abdomen pelvis
Dose - 0.6 mSv

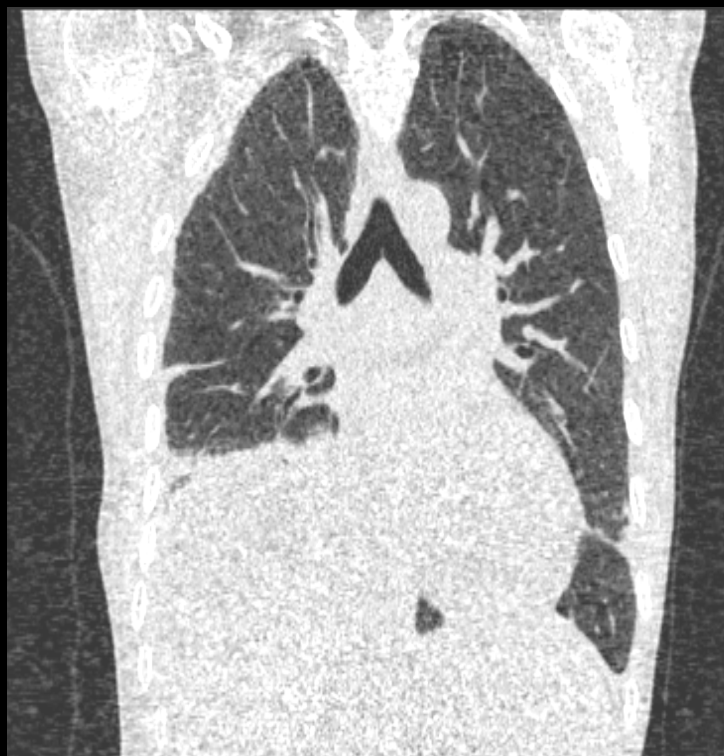
DLP 35, 0.625 mm
100 kVp, 25-38 mA

FBP Reconstruction

MBIR/Veo Reconstruction

Routine chest CT at chest X-ray dose - 0.09 mSv

DLP 6.3, 0.625 mm
100 kVp, 10 mA



FBP Reconstruction

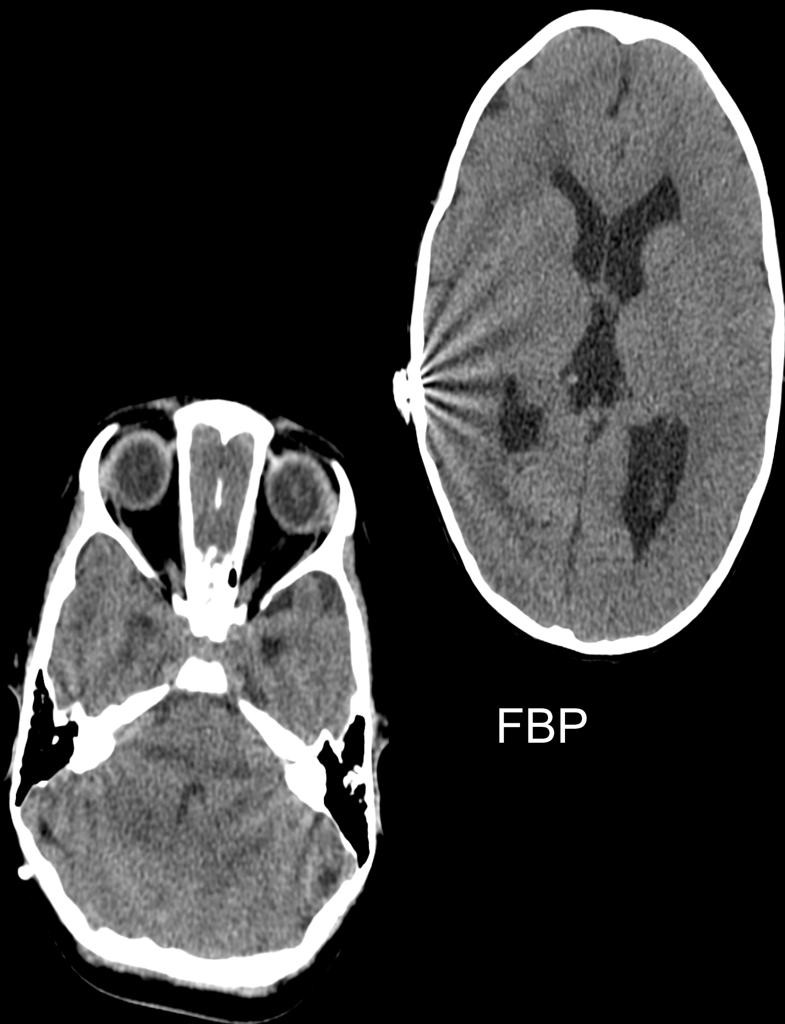
MBIR/Veo Reconstruction

"Typical CXR effective dose is about 0.06 mSv."

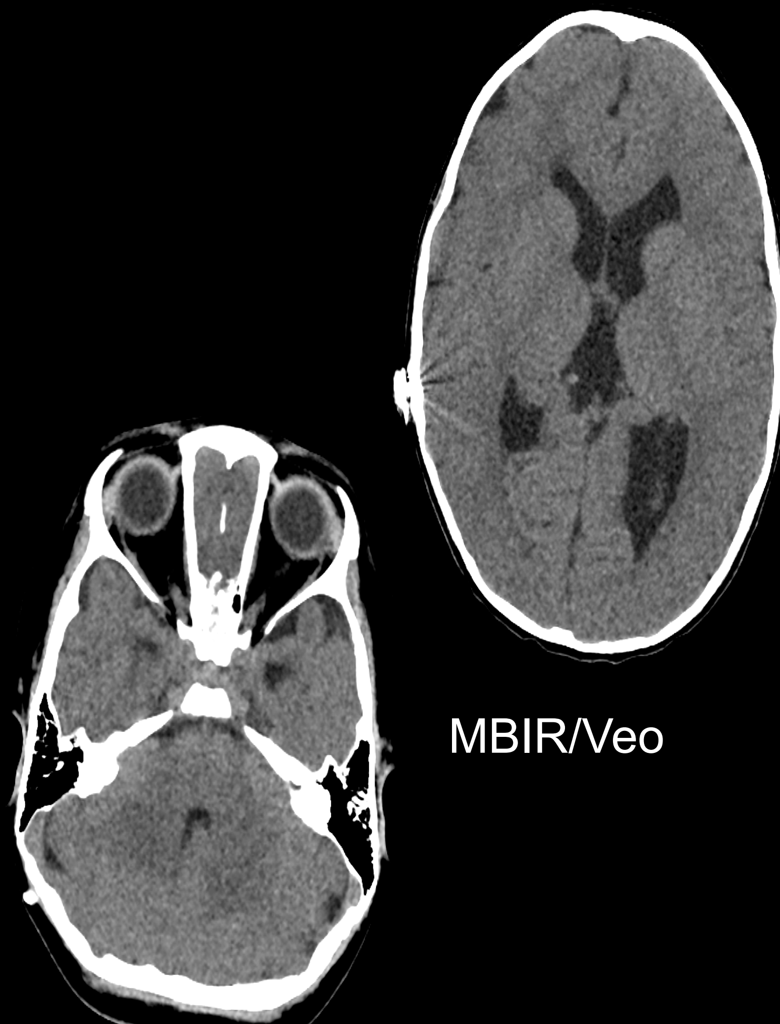
Source: Health Physics Society.
http://www.hps.org/publicinformation/ate/q2372.html

Routine head
ultra low dose - 0.5 mSv*

241 DLP, 0.625 mm
120 kVp, NI 3.0 (120-226 mA)



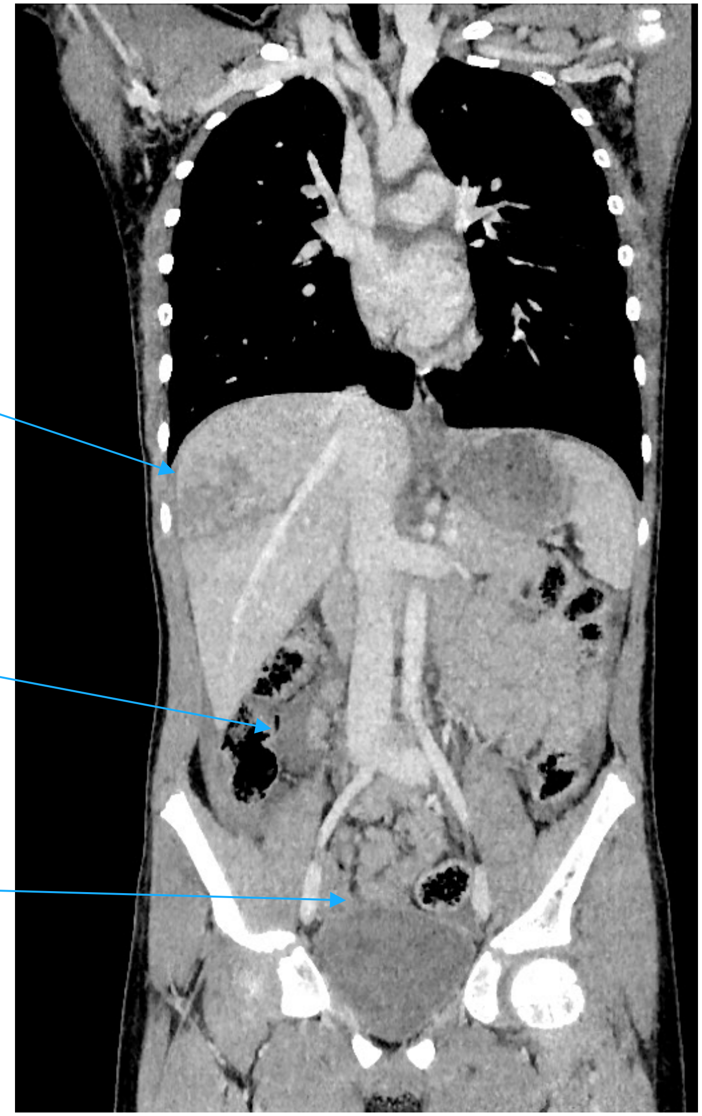
FBP



MBIR/Veo

Pediatric Image at Low Dose (Coronal)

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

Pediatric Image at Low Dose (Transverse)

ASiR Reconstruction

MBIR Reconstruction

Images courtesy of The Queen Silvia Children's Hospital

Dr. Stålhammar

VÄSTRA GÖTALANDSREGIONEN

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

Abdomen Imaging

FBP Reconstruction

MBIR Reconstruction

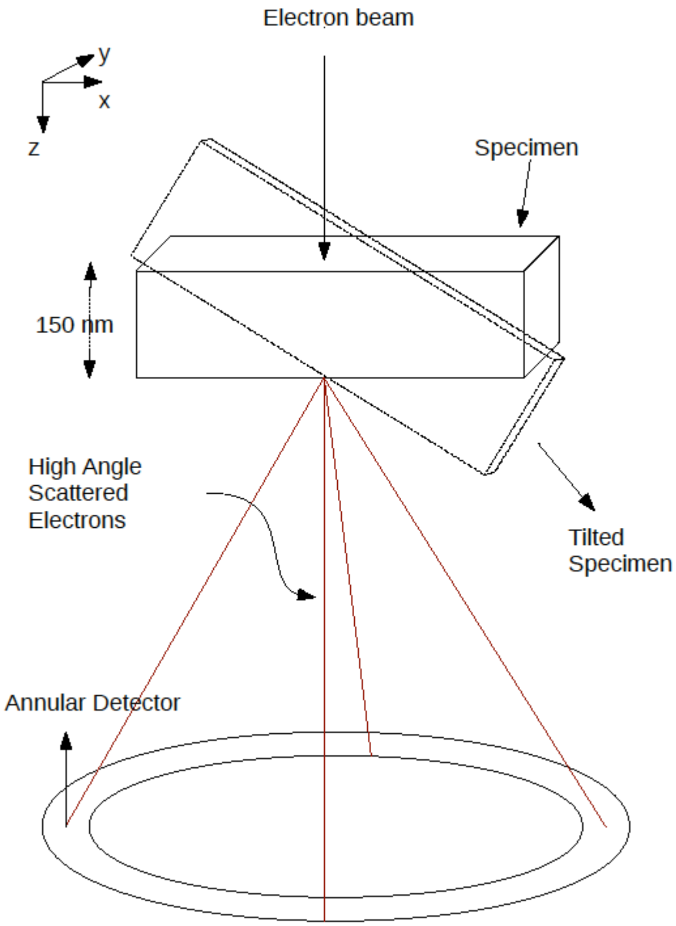
kV 120, mA 150, 0.5s, 0.625mm, WW 350 WL 50 DFOV 42 Standard kernel in FBP

Images courtesy of Dr Gladys Lo

MAP Reconstruction For Microscopy

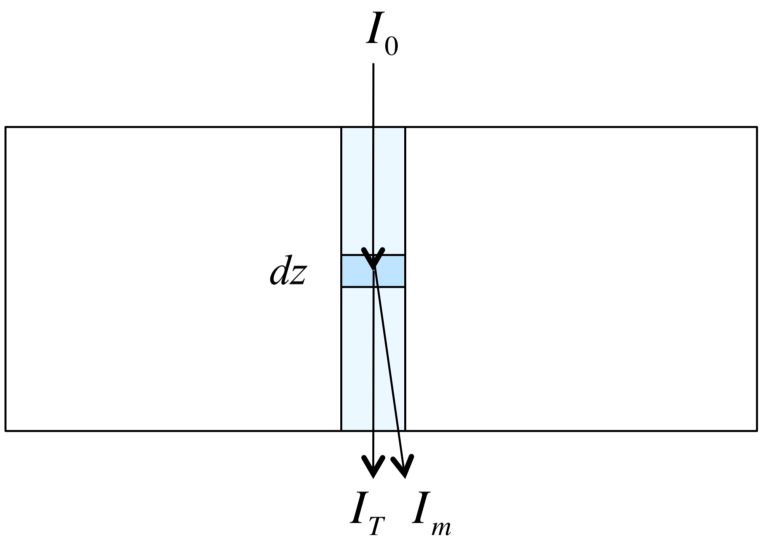
- Darkfield STEM
  - High Angle Annular Dark Field (HAADF)
  - Tilt axis parallel beam tomography
  - Obeys emission tomography forward model
- X-Ray Microscopic Imaging
  - Axial cone beam tomography problem
  - Obeys transmission tomography forward model
- Prior modeling of materials
  - MRF models
  - Sparse manifold methods
- Time varying tomography
  - Reconstruction from sparse measurements
  - Imaging dislocation structures

High Angle Annular Dark Field (HAADF) STEM Tomography



- Acquisition
  - An electron beam is focused at a point on the sample.
  - An annular ring detects elastically scattered electrons, but angle is small.
- Geometry
  - Electron beam is scanned across sample
  - Sample is tilted in one axis
  - Results in 2D parallel beam data

HAADF Measurement Model



Scattering coefficient:

$$s(z) = \sigma(z) N(z)$$

Attenuation coefficient:

$$\mu(z)$$

Attenuation of unscattered beam

$$I(z) = I_0 \exp\left(-\int_0^z \mu(r)\,dr \right)$$

$$I_T \triangleq I(z)$$

Attenuation of scattered beam

$$\frac{dI_m}{dz} = \exp\left(-\int_z^T \mu(r)\,dr \right) I(z) s(z)$$

$$I_m = \int_0^T \exp\left(-\int_z^T \mu(r)\,dr \right) I(z) s(z)\,dz$$

Combing expressions

$$I_m = I_T \int_0^T s(z)\,dz$$

So for homogeneous case with $\mu(z) = 0$ [Pennycook,1986], we have

$$I_m = I_T \sigma N T$$

HAADF Statistical Forward Model

- Follows emission tomography equations
  - I_m is Poisson so

$$E[I_m] = Var[I_m] = I_T \int_0^T s(z)\,dz$$

  - I_T must be determined through calibration or estimation

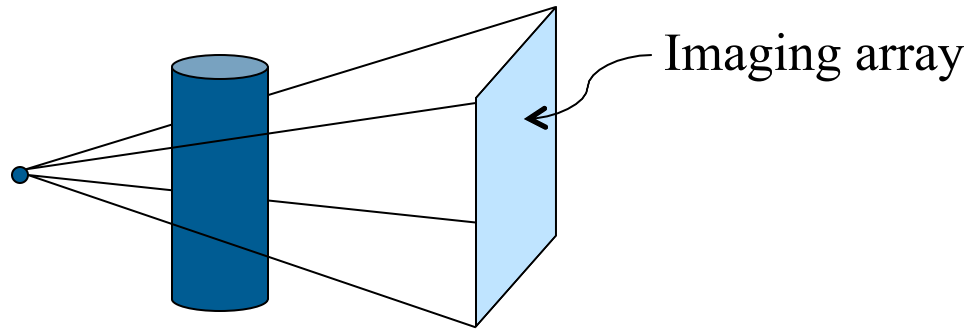
- MAP reconstruction is given by

$$\hat{x} = \arg\min_{x \geq 0} \left\{ (y - Ax)^t \Lambda (y - Ax) + S(x) \right\}$$

where

$$y_i = I_{m,i} \text{ and } \Lambda_{i,i} = \frac{1}{I_{m,i}}$$

X-Ray Cone Beam Transmission Tomography



- Geometry
  - X-ray source forms cone-beam
  - Axial rotation provides 3D data
- Acquisition
  - Measurements are Poisson
  - Beer's law can be used to compute density integral

$$E[\lambda_i] = \lambda_{0,i} \exp\left(-\int_0^T \mu(r) dr \right)$$

X-ray Transmission Statistical Forward Model

- Follows transmission tomography equations
  - λ_i is Poisson
  - $\lambda_{0,i}$ must be determined through calibration or estimation

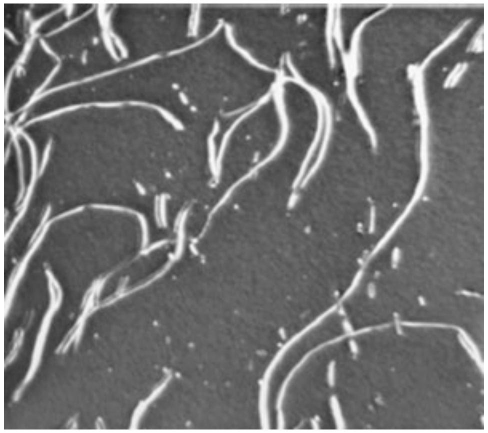
- MAP reconstruction is given by

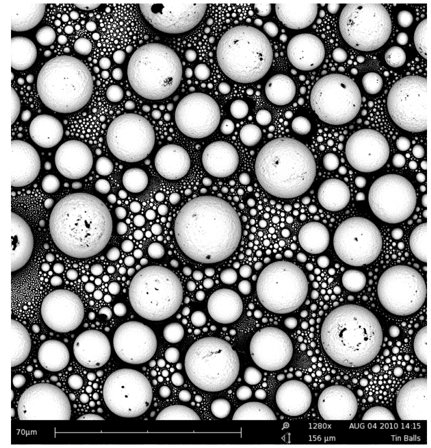
$$\hat{x} = \arg\min_{x \geq 0} \left\{ (y - Ax)^t \Lambda (y - Ax) + S(x) \right\}$$

where

$$y_i = -\log\left(\frac{\lambda_i}{\lambda_{0,i}}\right) \text{ and } \Lambda_{i,i} = \lambda_i$$

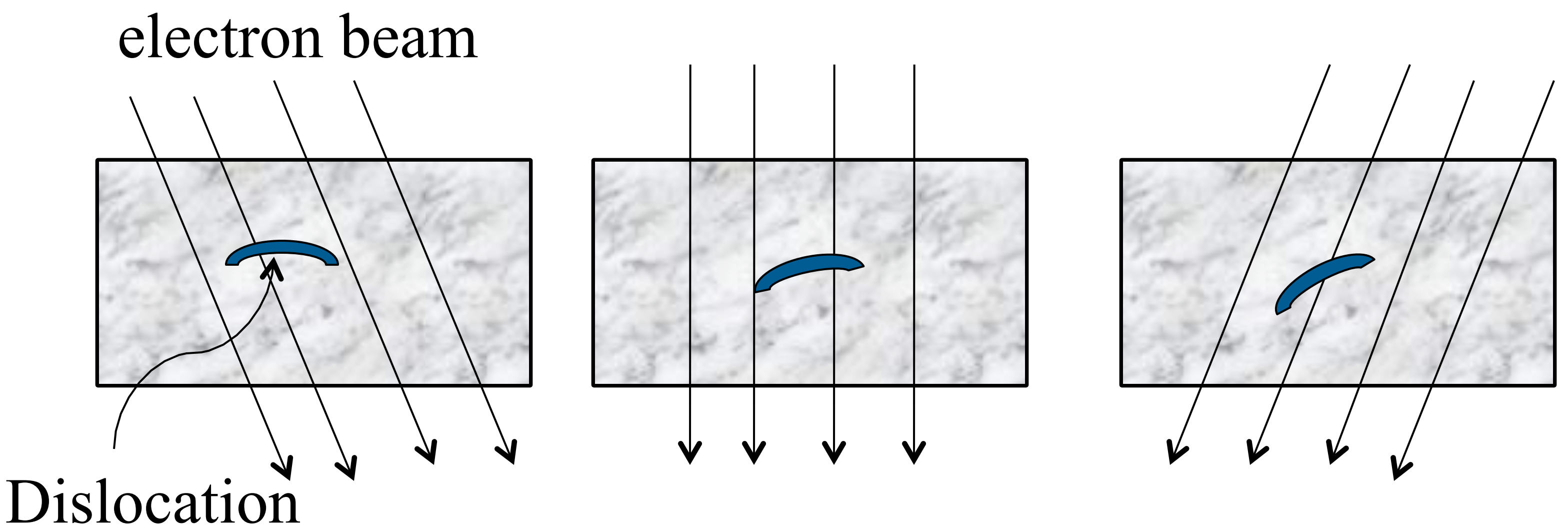
Material Prior Models





- Enormous amount of structure to exploit
  - Repeated morphology
  - Thin manifolds
  - Underlying physics
- How can this be effectively modeled?
  - Markov random field (MRF) priors
  - Sparse subspaces using over-complete bases
  - Dictonary-based learning
  - Manifold learning

Time Varying Tomography



- Assumptions
  - Time varying structure
  - Time varying measurements
- Sparse reconstruction
  - Number of additional unknowns is small
  - Reconstruction only requires a small number of additional measurements

Project Objectives

- Implement MAP reconstruction for HAADF tomography
- Develop prior models for real materials
- Formulate time varying reconstruction problem