

Sinogram restoration for computed tomography

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Patrick La Rivière, Ph.D.
Associate Professor
Department of Radiology
The University of Chicago



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Conclusions

- Sinogram restoration is a statistically principled way of preprocessing CT data prior to reconstruction by analytic algorithms
- It can not only be used to reduce artifacts (the point of most preprocessing) but also to reduce noise and model geometric effects, as in fully iterative algorithms.
- At the very least, it represents a computationally efficient middle ground between analytic algorithms and fully iterative ones.
 - However, in many studies we have done it performs as well as fully iterative algorithms.
 - It can readily accommodate the proper “nonlinear” model for CT. Many/Most fully iterative algorithms work with linearized system models.
- Naturally it has limitations: harder to accommodate non-negativity and other constraints, harder to implement edge-preserving priors.

Outline

- Overview of data degradations in CT
- Development of an imaging model
- Introduction of our sinogram restoration strategy
- Results of a collaboration with Philips
- Deeper connections between iterative sinogram-domain methods and fully iterative image reconstruction

Ideal imaging model in CT

- In CT we seek to reconstruct the X-ray attenuation map from measurements of X-ray transmission along a number of lines.
- Reconstruction algorithms such as filtered backprojection (FBP) assume

$$I_i^{\text{det}} = I_i^{\text{inc}} e^{-l_i}$$

where

$$l_i = \int_{L_i} \mu(\vec{x}) dl$$

Deviations from the model

- Noise
- Beam hardening
- Scatter
- Off-focal radiation
- Detector speed and afterglow
- Detector crosstalk
- Detector dark current
- Metal artifacts

Noise-induced streak artifacts

At low doses, high noise levels in the most attenuated projections can lead to distracting noise-induced streaks.

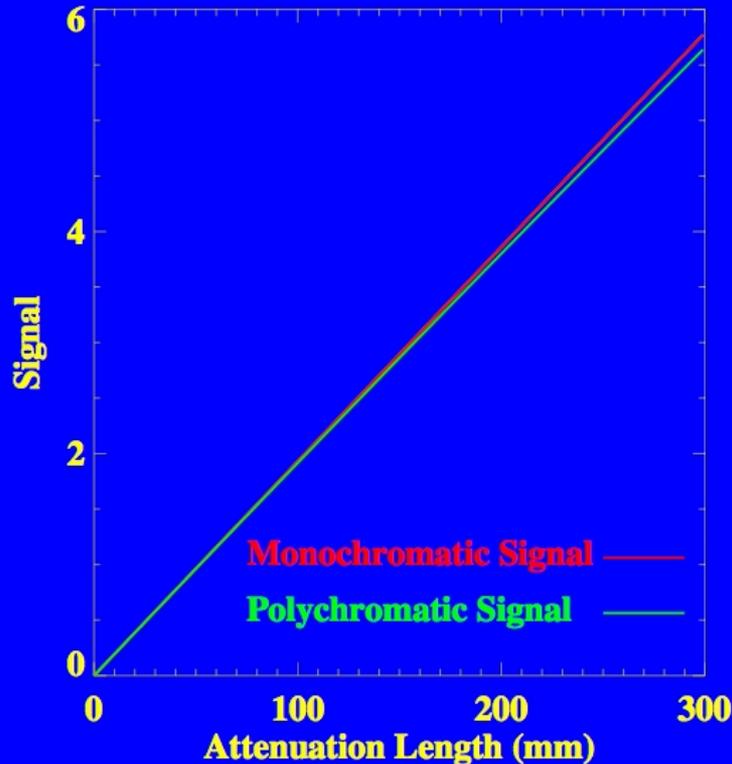


No adaptive filtering



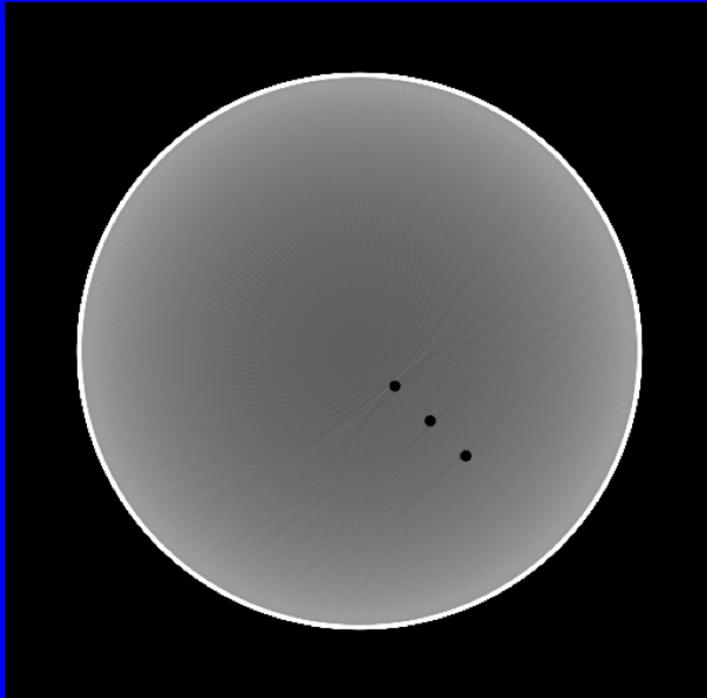
Penalized-likelihood
sinogram smoothing

Beam hardening

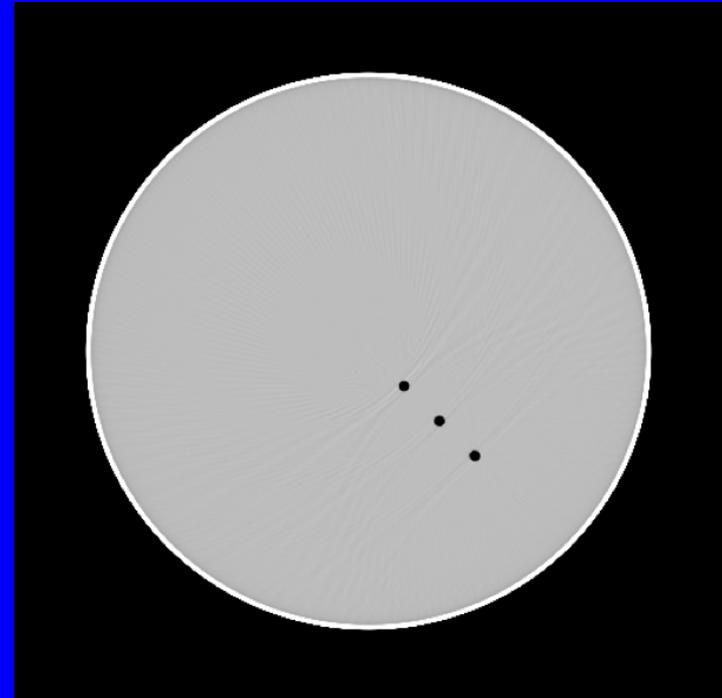


For water-equivalent materials (i.e., most soft tissues) the effect of beam hardening is a slight non-linearity in the detected signal, which is given by the green line at left rather than the ideal red line.

Effect of beam hardening



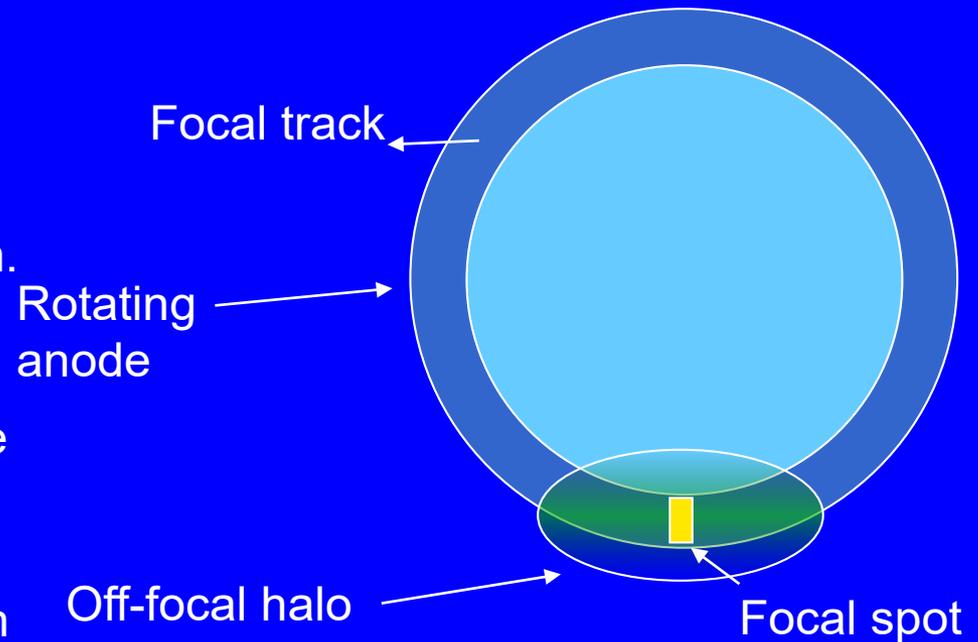
No correction



Correction by line-integral remapping

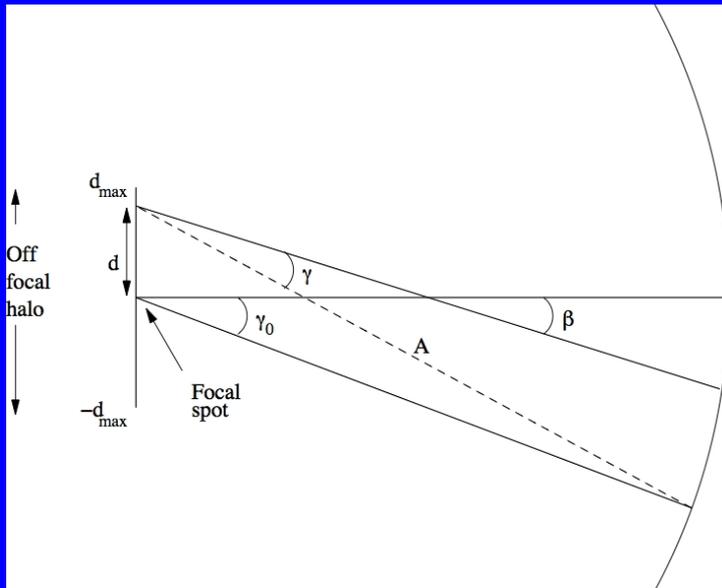
Off-focal radiation

- The vast majority of x-rays emerge from the small focal spot of the tube, but a lower-intensity halo of off-focal x-rays typically surrounds them.
- These arise when secondary electrons escape the focal spot and strike the elsewhere on the anode.
- If not accounted or corrected for, this off-focal radiation can lead to halo-like artifacts at boundaries in reconstructed images.

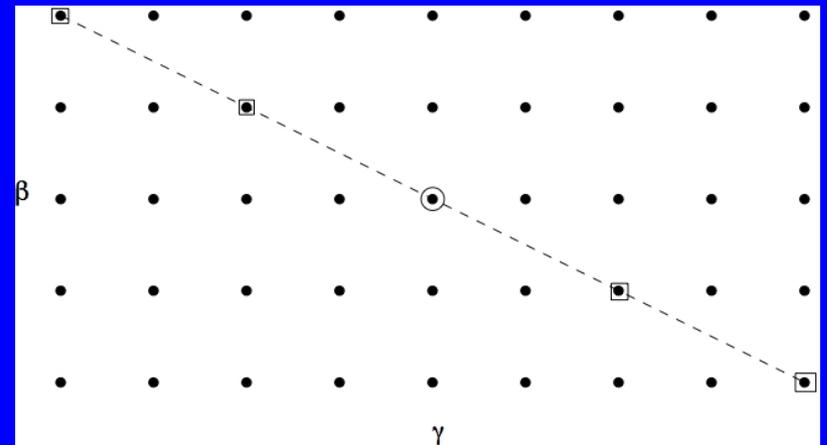


Schematic of off-focal radiation

Off-focal radiation

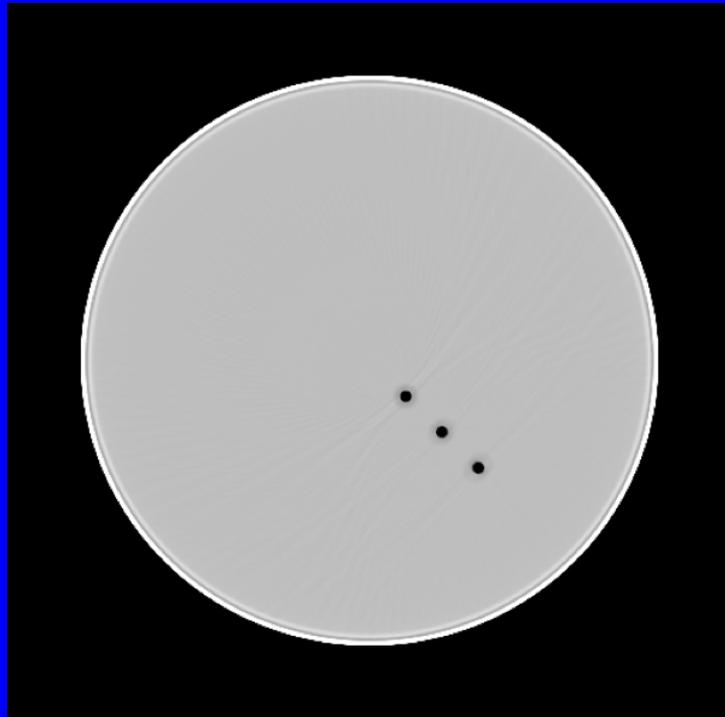


Geometry of off-focal radiation

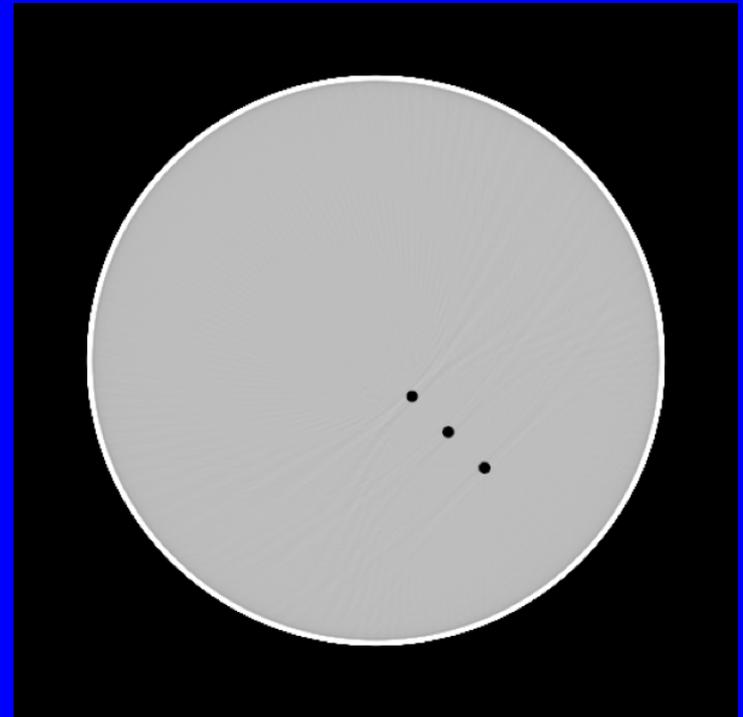


Off-focal radiation = convolution in sinogram

Effect of off-focal radiation



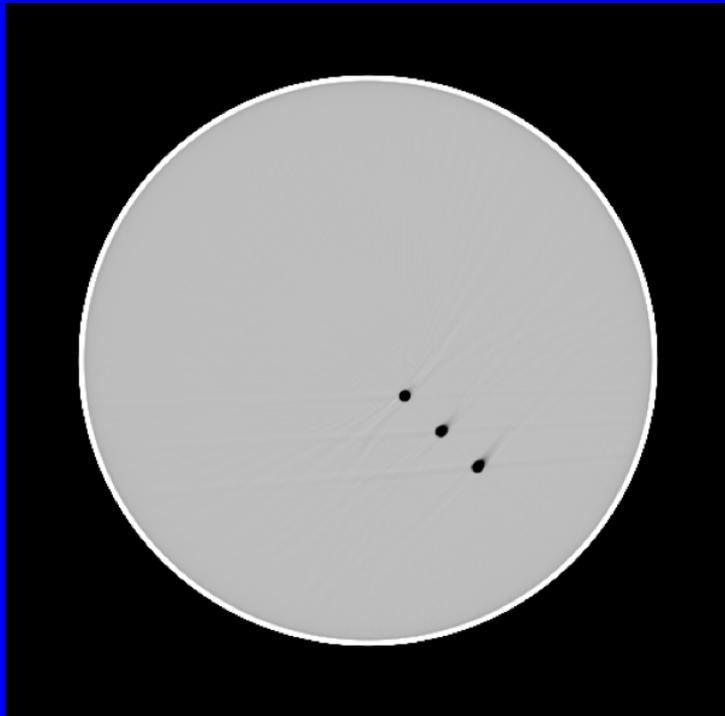
No correction



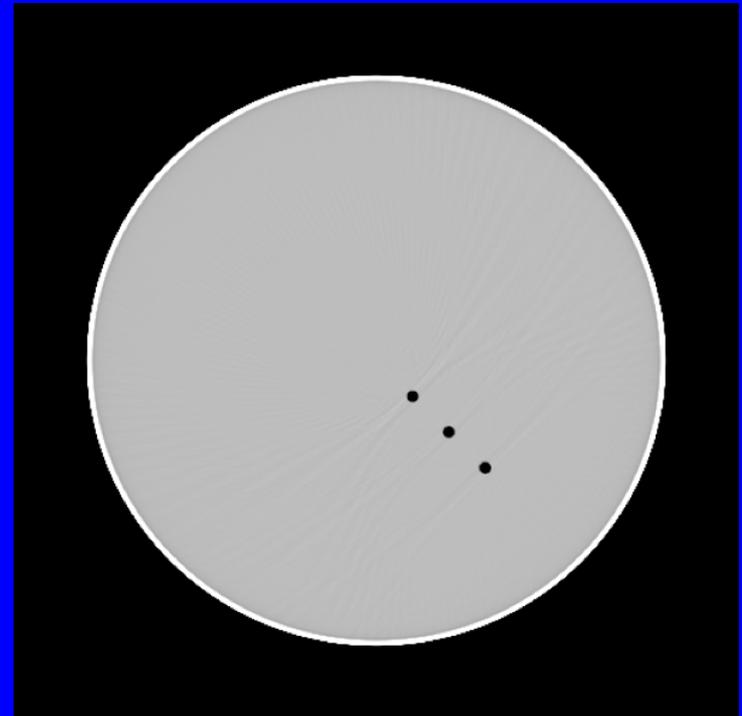
Correction by
deconvolution

Afterglow

- If detector “lag” is on the order of detector sampling rate, signal blurs from one projection to the next.
- Detectors are getting faster but so is sampling rate (flying focal spot, faster gantries, etc).

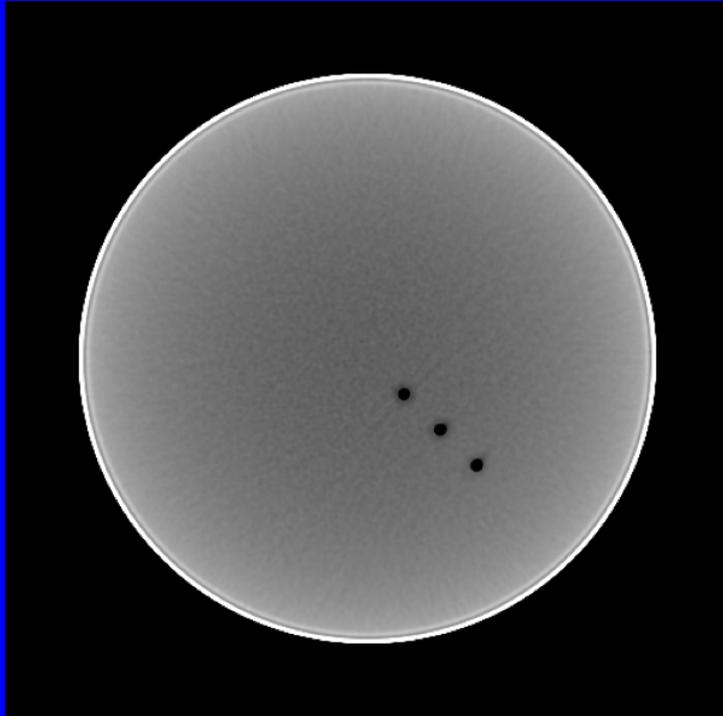


No correction

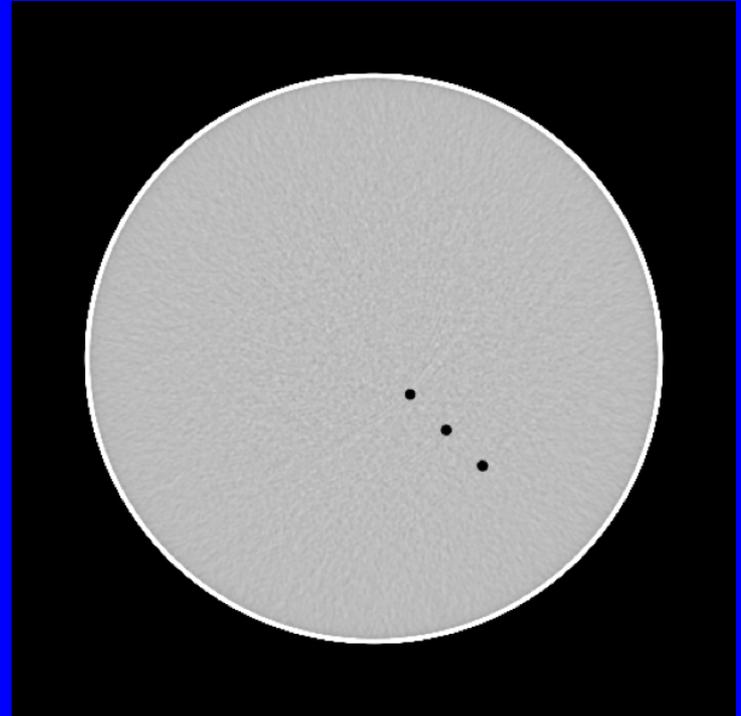


Recursive correction

All the effects

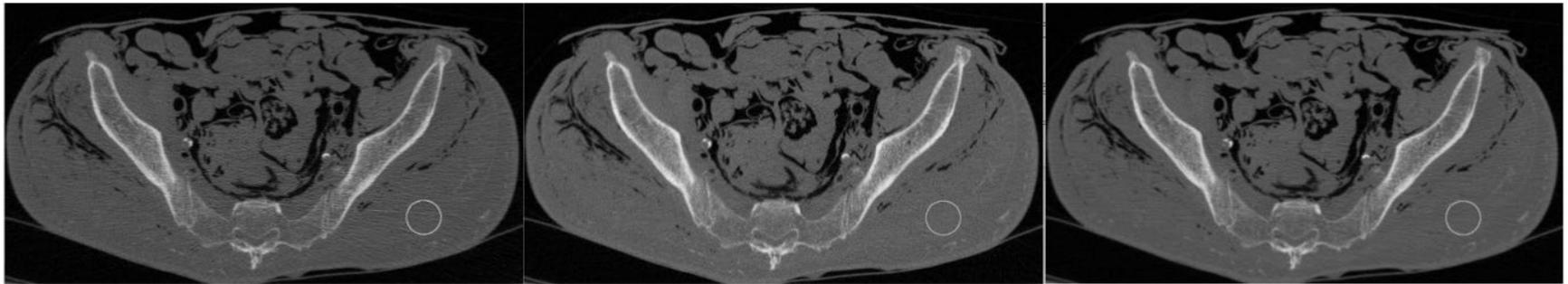


No correction



Penalized-likelihood
correction

Examples: potential for dose reduction



(a) 35 mA, standard, s. dev. = 153.3

(b) 35 mA, proposed PL, s. dev. = 99.4

(c) 75 mA, standard, s. dev. = 87.15



(d) 35 mA, standard, s. dev. = 241.9

(e) 35 mA, proposed PL, s. dev. = 98.0

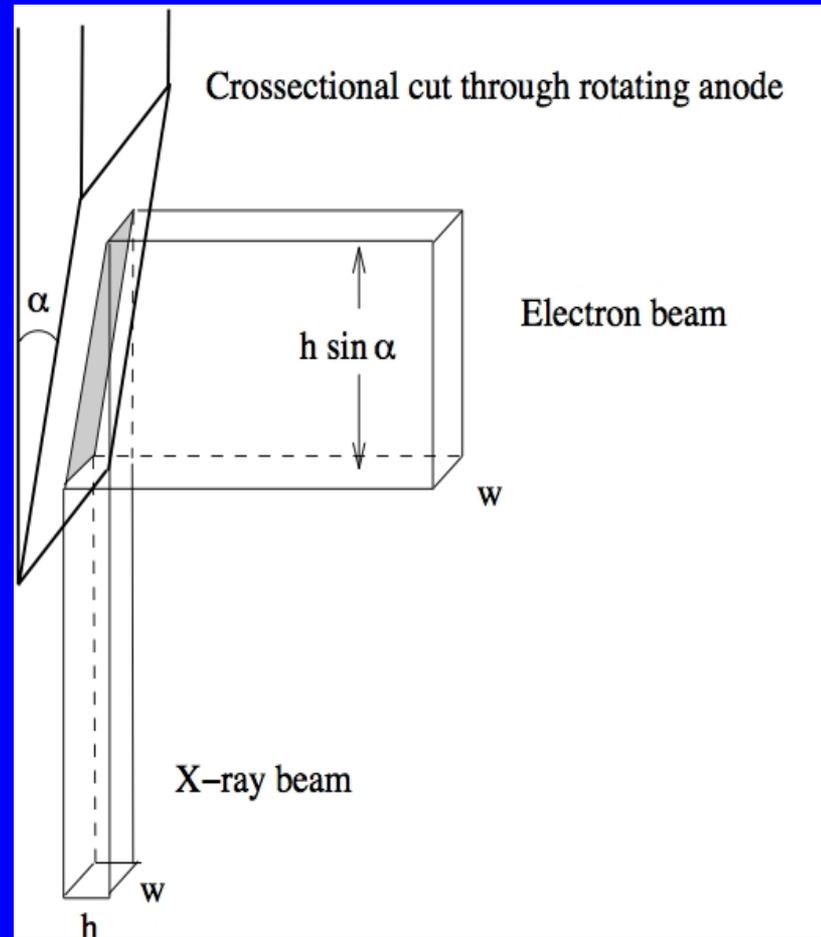
(f) 75 mA, standard, s. dev. = 119.3

Examples: potential for artifact reduction



An aside on geometry modeling

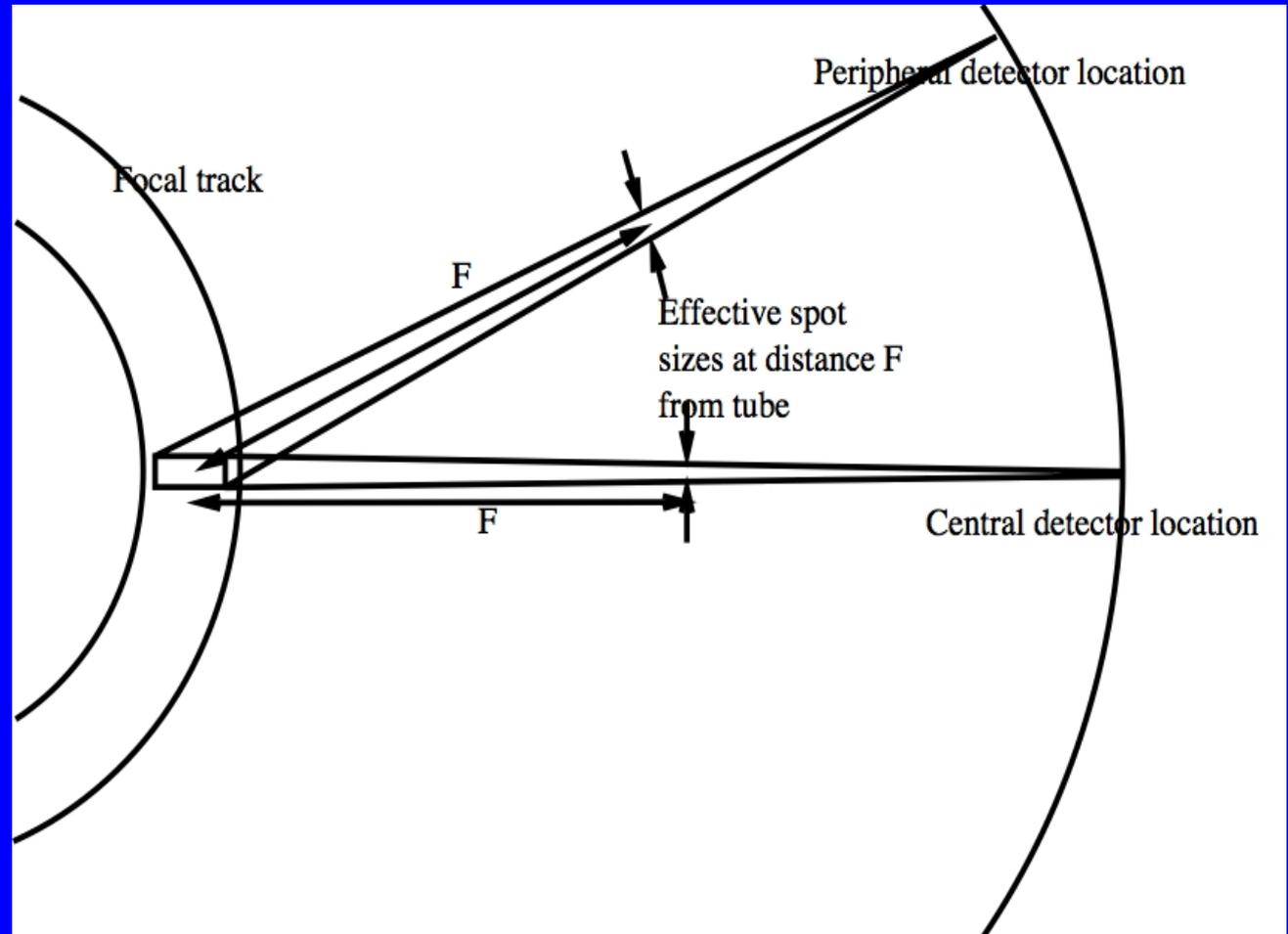
- Heat generation in X-ray tubes is a significant limiting factor.
- ♦ To allow heat generated to be spread over a wider area, the anode is rotated and the focal track is also beveled at a shallow angle.
- ♦ Thanks to the line focus principle, this allows a fairly large area of the focal track to be exposed to electrons while retaining a fairly small effective projected focal spot.



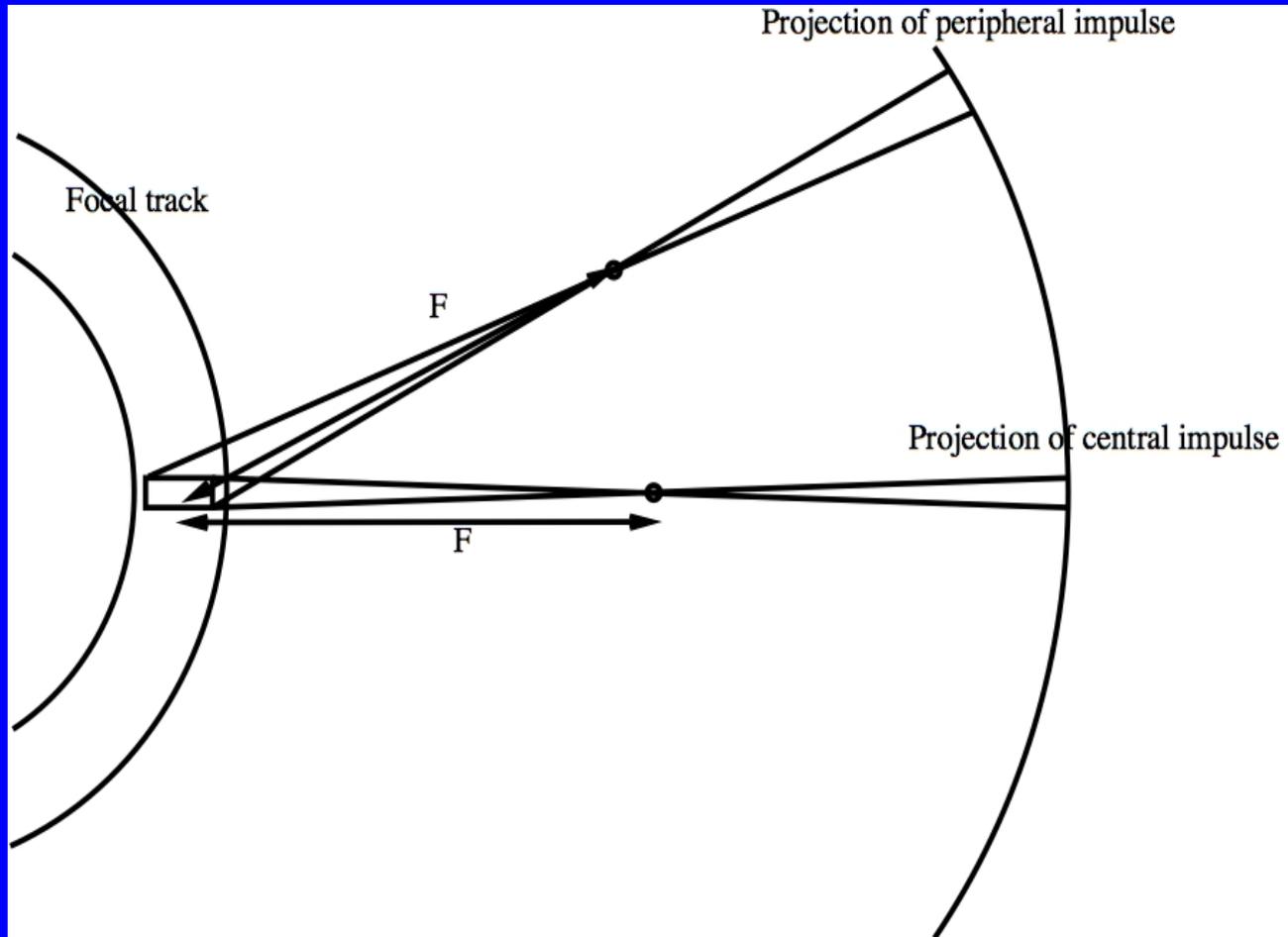
$\alpha \sim 5-7$ degrees in CT tubes

Differential focal spot size

- Focal spot appears larger to peripheral detectors: this leads to spatially varying spatial resolution.
- Our goal is to model and correct for this in the sinogram domain using penalized likelihood sinogram restoration.

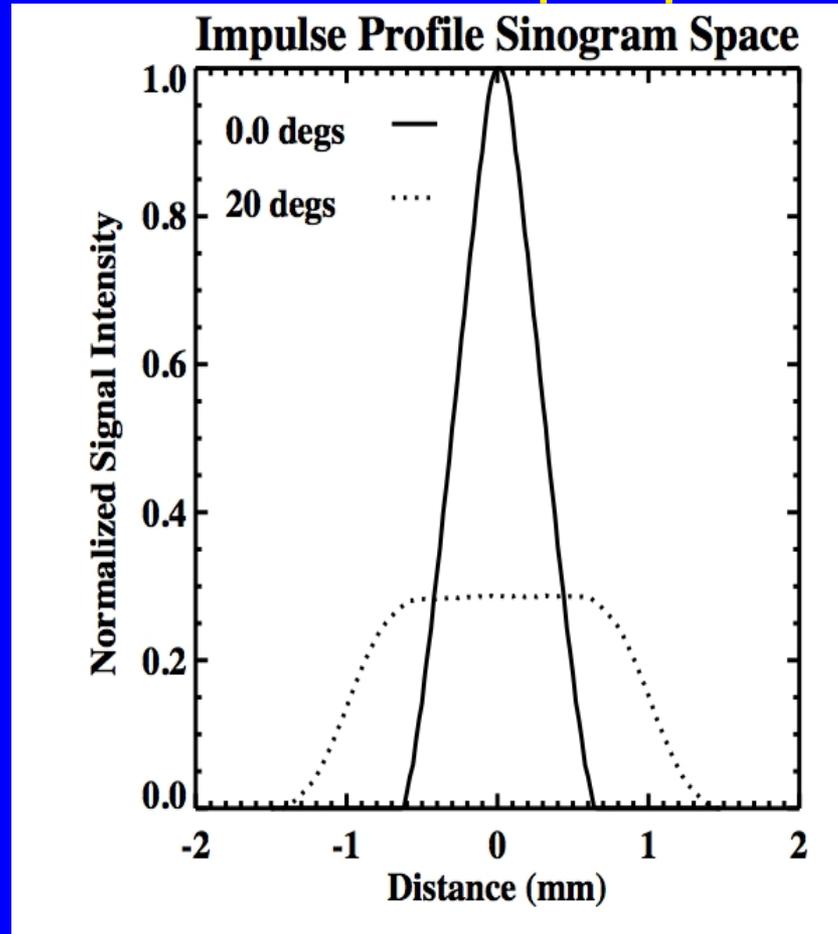


Differential projection of impulse



So a peripheral impulse will produce a broader projection

Projection of central and peripheral impulses



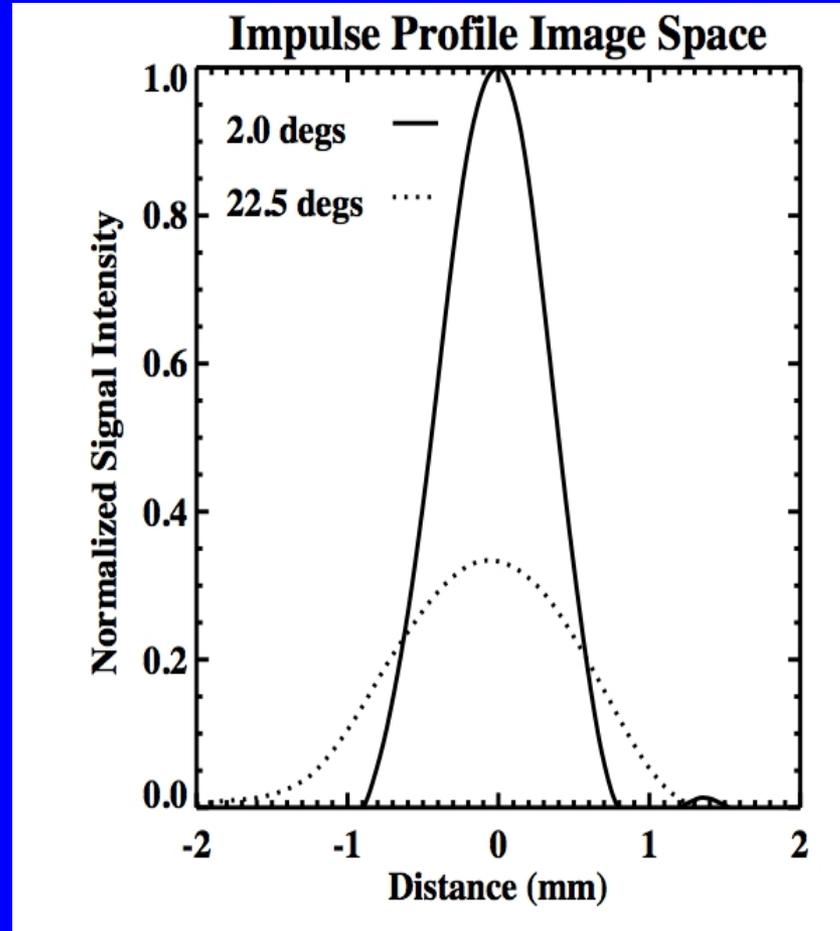
Peripheral projection has been superimposed on central projection so they may be compared

See similar figure in Jiang Hsieh's book *Computed Tomography*.

Peripheral impulse produces a broader projection

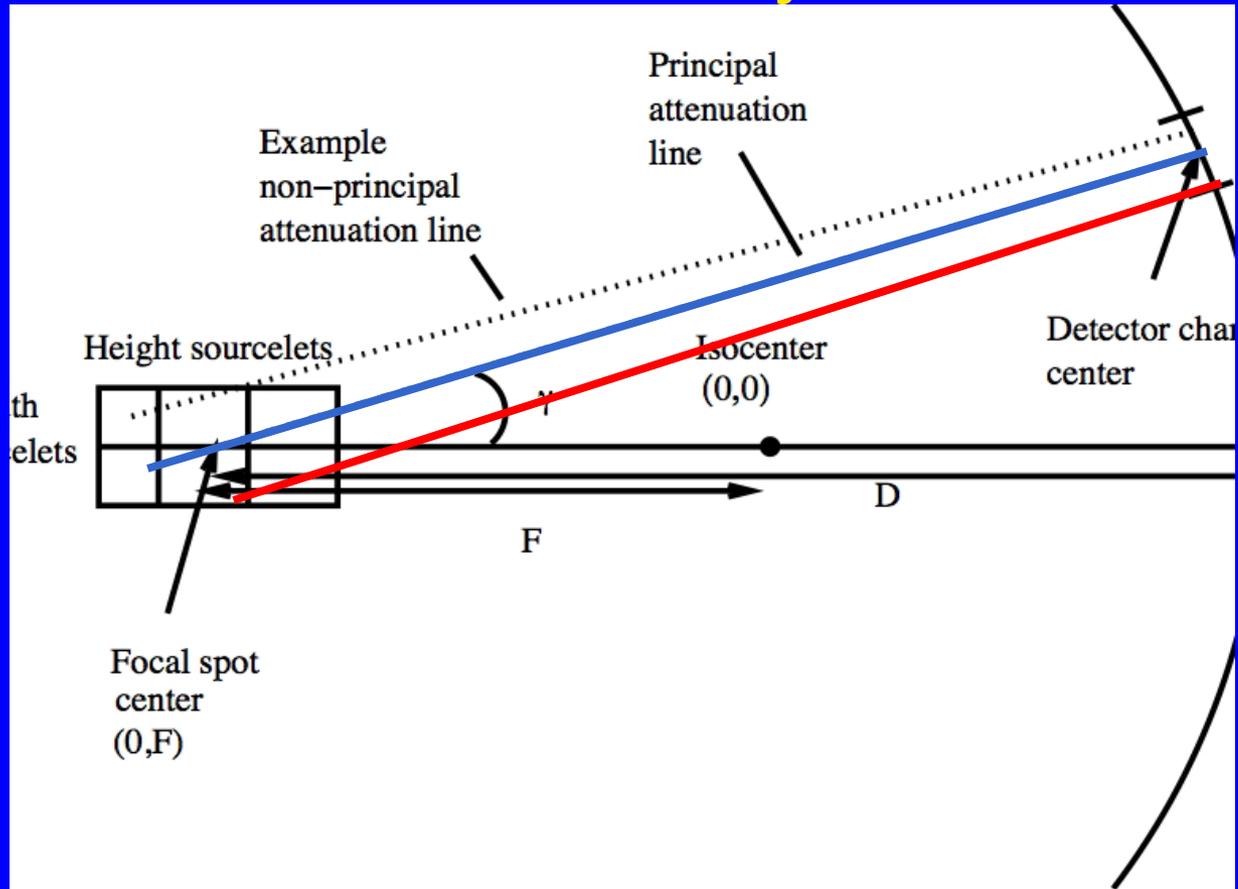
Reconstruction of central and peripheral impulses

Profiles through reconstructions of central and peripheral impulses have been superimposed for comparison



Peripheral impulse produces a broader reconstruction

Geometry

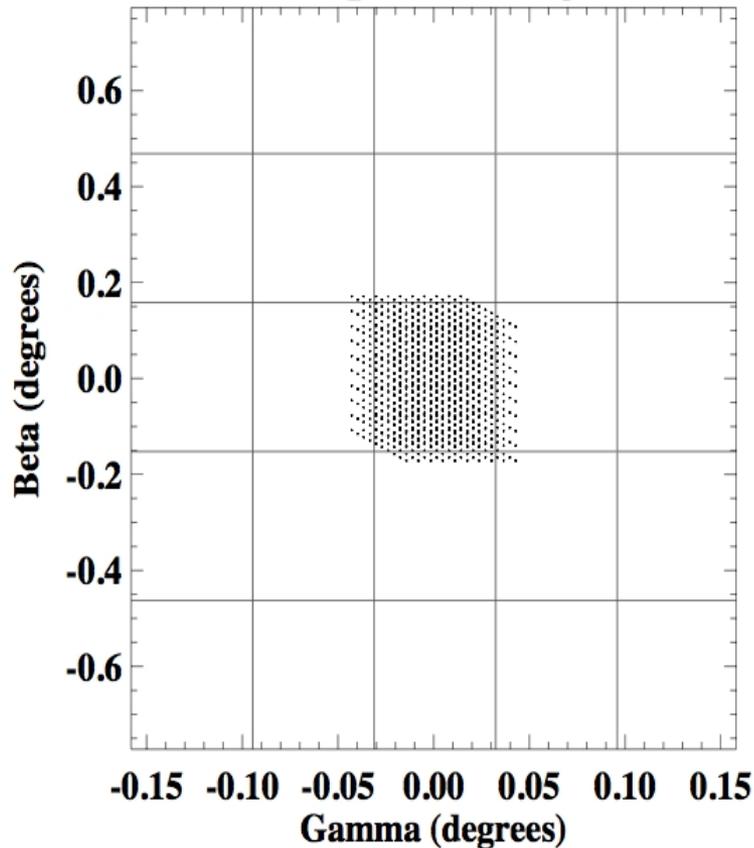


Measurement involves average over (exponentiated) line integrals having a range of different fanbeam coordinates. We can calculate those coordinates and make a scatterplot.

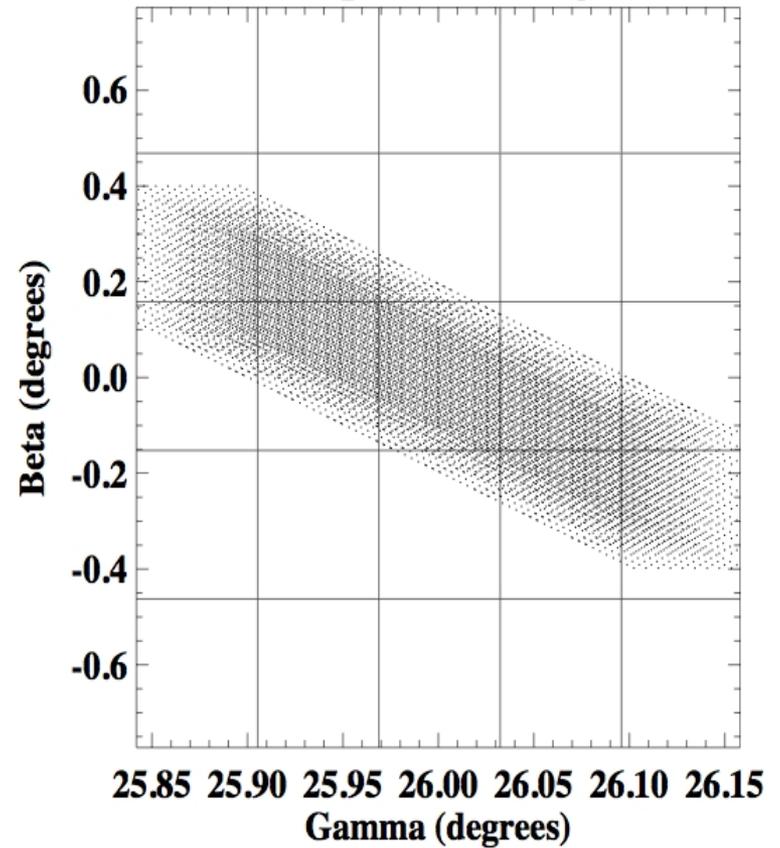
Scatterplot of effective line integral

dir

Scatterplot at 0 degrees



Scatterplot at 26 degrees



Linear vs nonlinear modeling

- This kind of geometric modeling can be represented as

$$y_i = \iint d\gamma d\beta I(\gamma, \beta) f_i(\gamma, \beta) e^{-\int \mu(x, y) d\ell}^{L(\gamma, \beta)}$$

Incident intensity

Effective measurement kernel

- We can discretize the attenuation map yielding

$$y_i(\vec{x}) = \sum_j b_{ij} e^{-\sum_k a_{jk} x_k}$$

- **KEY POINT:** The coefficients a_{jk} represent intersections of LINES with basis functions.

Linear vs. nonlinear modeling

As far as I know, no one is working with this equation:

$$y_i(\vec{x}) = \sum_j b_{ij} e^{-\sum_k a_{jk} x_k}$$

Instead, people use one of three major approaches:

1) The use of raw data but with a single linear approximate matrix:

$$y_i = I_i e^{-\sum_k c_{ik} x_k}$$

2) The use of logged data and a single linear approximate matrix:

$$z_i = -\ln\left(\frac{y_i}{I_i}\right) = \sum_k c_{ik} x_k$$

3) Sinogram restoration, using the first eq. to estimate ideal line integrals, which are then used in FBP:

$$y_i = \sum_j b_{ij} I_j^{(ideal)}, \text{ where } I_j^{(ideal)} = I_j e^{l_i}$$

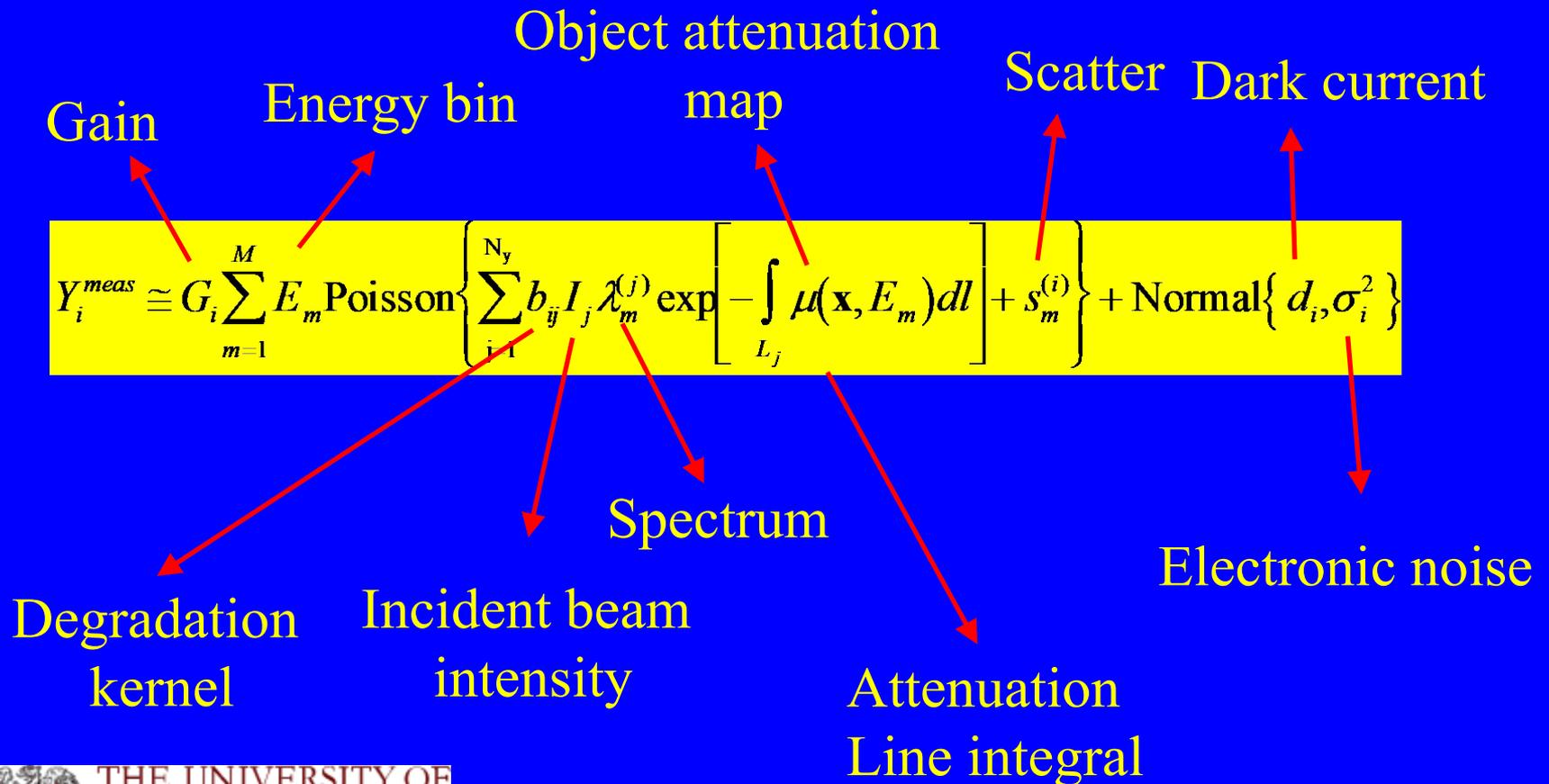
Sinogram restoration for focal spot

- One could conceivably try to deconvolve the focal spot effect entirely.
 - This kind of superresolution approach is likely to be highly ill-posed.
- A more reasonable strategy is to attempt to *equalize* resolution across the sinogram by compensating for the differential focal spot effects.
 - To do this, we discretize the scatter plots by smoothing and subsampling to obtain coefficients linking the target, uniform-resolution sinogram to the measured, non-uniform resolution sinogram.
- I..e. we seek coefficients b_{ij} such that we can write:

$$I_i^{(meas)} = \sum_j^{N_y} b_{ij} I_j^{(unif)}$$

An imaging model

- We assume the CT scan produces a set of measurements that are realizations of random variables:



A simplified imaging model

- More practically, we assume the CT scan produces a set of measurements that are realizations of random variables:

Beam hardening function

$$Y_i^{meas} \cong G_i \bar{E}_i \text{Poisson} \left\{ \sum_{j=1}^{N_y} b_{ij} I_j e^{-f_j(l_j)} + \bar{s}_i \right\} + \text{Normal} \{ d_i, \sigma_i^2 \}$$

$$\bar{E}_i = \sum_{m=1}^M E_m \lambda_m^{(i)}$$

$$l_i \equiv \int_{L_i} \mu(\mathbf{r}, \bar{E}_i) dl = A \mathbf{x}$$

$$\bar{s}_i = \frac{1}{E_i} \sum_{m=1}^M E_m s_m^{(i)}$$

Four potential strategies

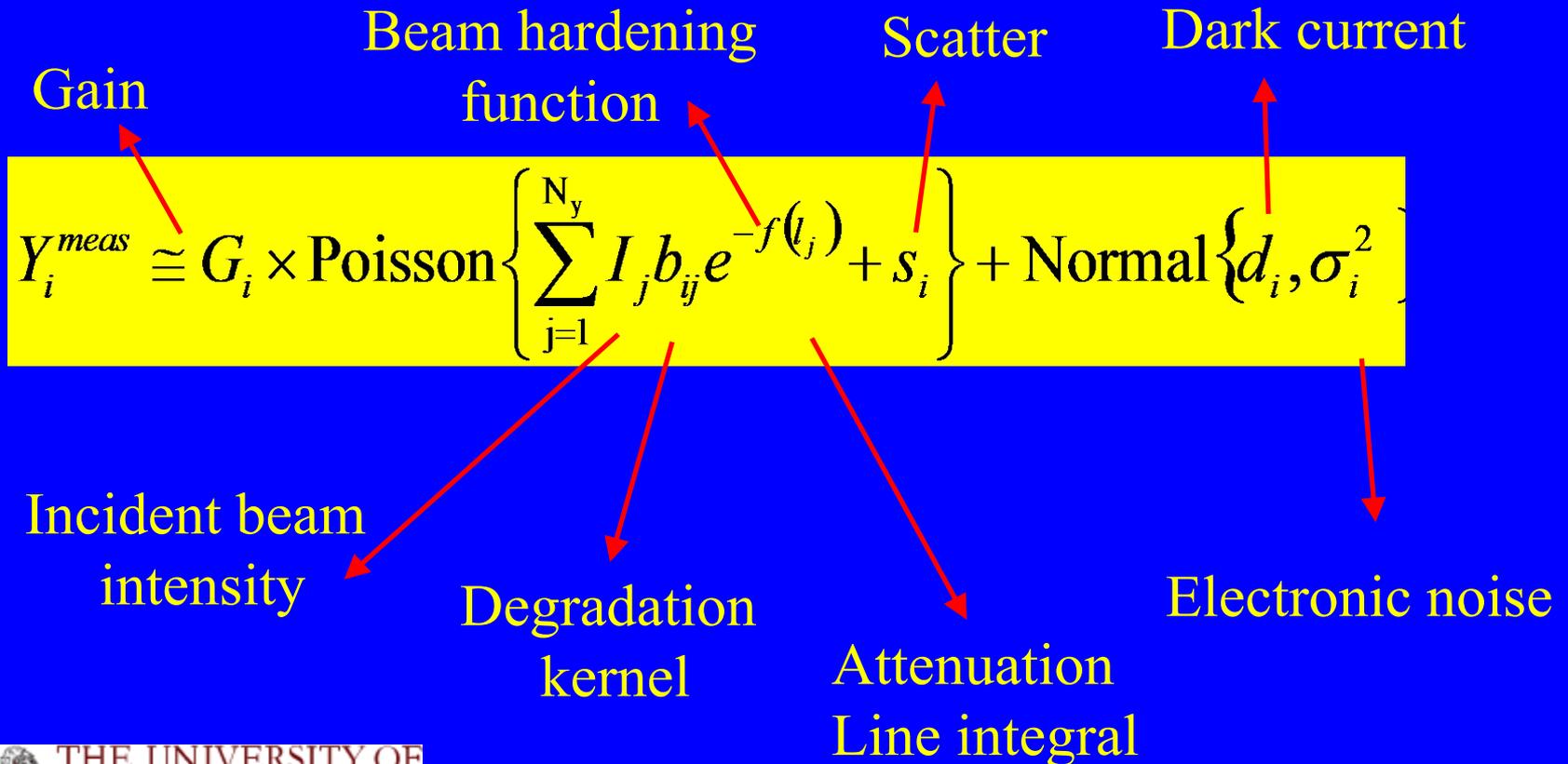
1. **Current commercial approach:** Attempt to estimate the line integrals from the data by standard sinogram preprocessing/calibration techniques and then use analytic reconstruction to obtain the image vector \mathbf{x} .
2. **Promising iterative approach:** Attempt to estimate the line integrals from the data by standard sinogram preprocessing/calibration techniques and then use iterative reconstruction with statistical modeling to obtain the image vector \mathbf{x} .
3. **Pipe dream iterative approach:** Use iterative reconstruction to estimate the image vector \mathbf{x} directly from the transmission measurements by modeling all effects.
4. **Our approach:** Use iterative methods with statistical modeling to estimate the line integrals and then use analytic reconstruction to obtain the image vector \mathbf{x} .

Our approach to sinogram processing

- We have formulated CT sinogram preprocessing as a statistical restoration problem.
 - The goal is to estimate as accurately as possible the attenuation line integrals needed for reconstruction from the set of noisy, degraded measurements.
 - We do so by maximizing a penalized-likelihood objective function.
 - Reconstruction is then done by use of existing methods.
- The hope is that one could achieve reduced noise and artifact levels relative to existing approaches, especially in low-dose and non-contrast scans.

Imaging model

- We assume the CT scan produces a set of measurements that are realizations of random variables:



Adjusted measurements

- The sum of a Poisson and a Gaussian does not produce a tractable likelihood function, so we define adjusted measurements that we assume to be Poisson:

$$Y_i \equiv \left[\left(\frac{Y_i^{meas} - d_i}{G_i} \right) + \frac{\sigma_i^2}{G_i^2} \right]$$
$$\cong \text{Poisson} \left\{ \sum_{j=1}^{N_y} I_j b_{ij} e^{-f(l_j)} + s_i + \frac{\sigma_i^2}{G_i^2} \right\}$$

- A similar approximation is employed by Snyder *et al.* in the context of CCD image restoration. (JOSA 1993)

Objective function

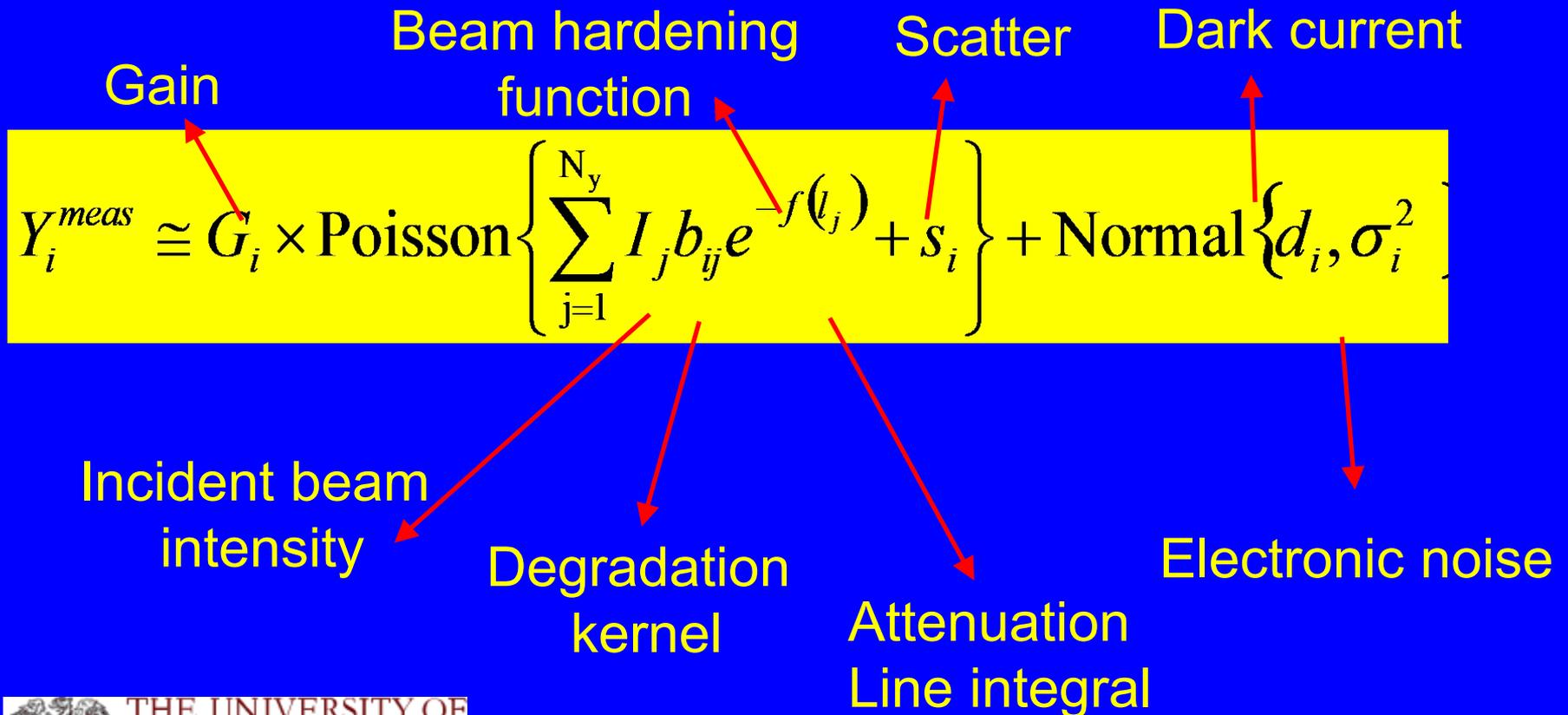
- We find the undegraded attenuation line integrals by

$$\hat{\mathbf{l}} = \arg \max_{\mathbf{l} \geq \mathbf{0}} [L(\mathbf{l}; \mathbf{y}) - \beta R(\mathbf{l})]$$

- Here $L(\mathbf{l}; \mathbf{y})$ is the Poisson likelihood for the adjusted measurements \mathbf{y} and $R(\mathbf{l})$ is the roughness penalty.
- To maximize we make use of an update derived by use of the optimization transfer approach (Fessler, 2000) adapting some tricks due to DePierro (1995).

Penalized likelihood sinogram restoration

- Perform a sinogram-domain penalized likelihood estimate of ideal line integrals needed for reconstruction.

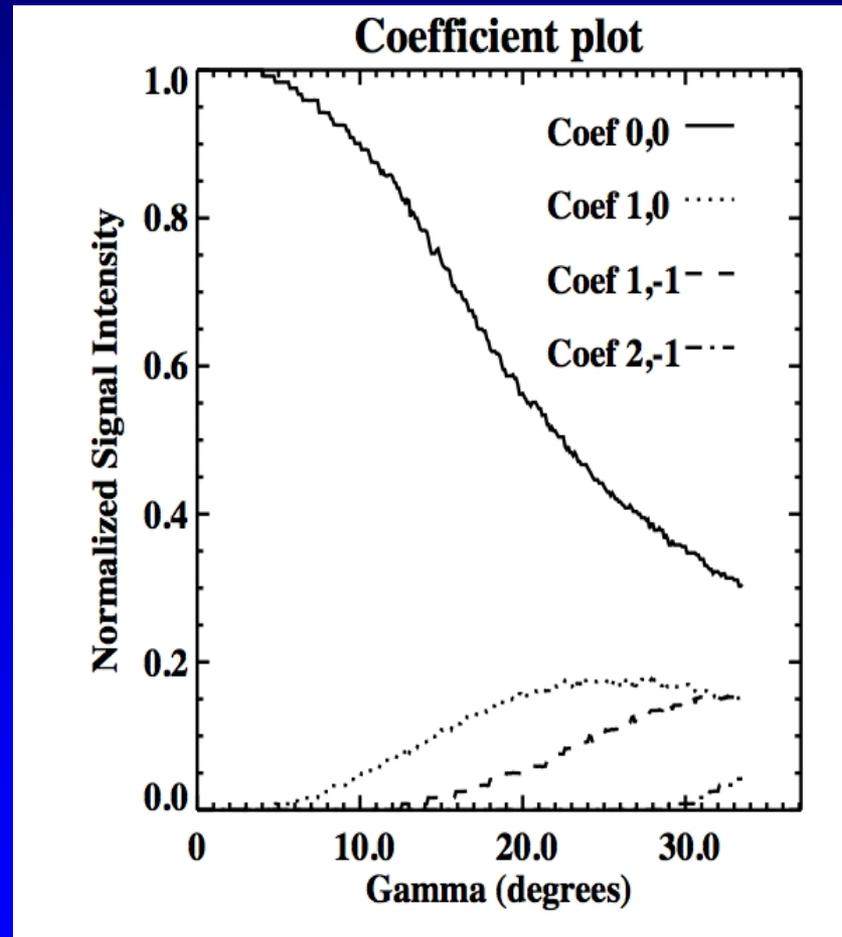


Plot of coefficients versus angle in fanbeam

β

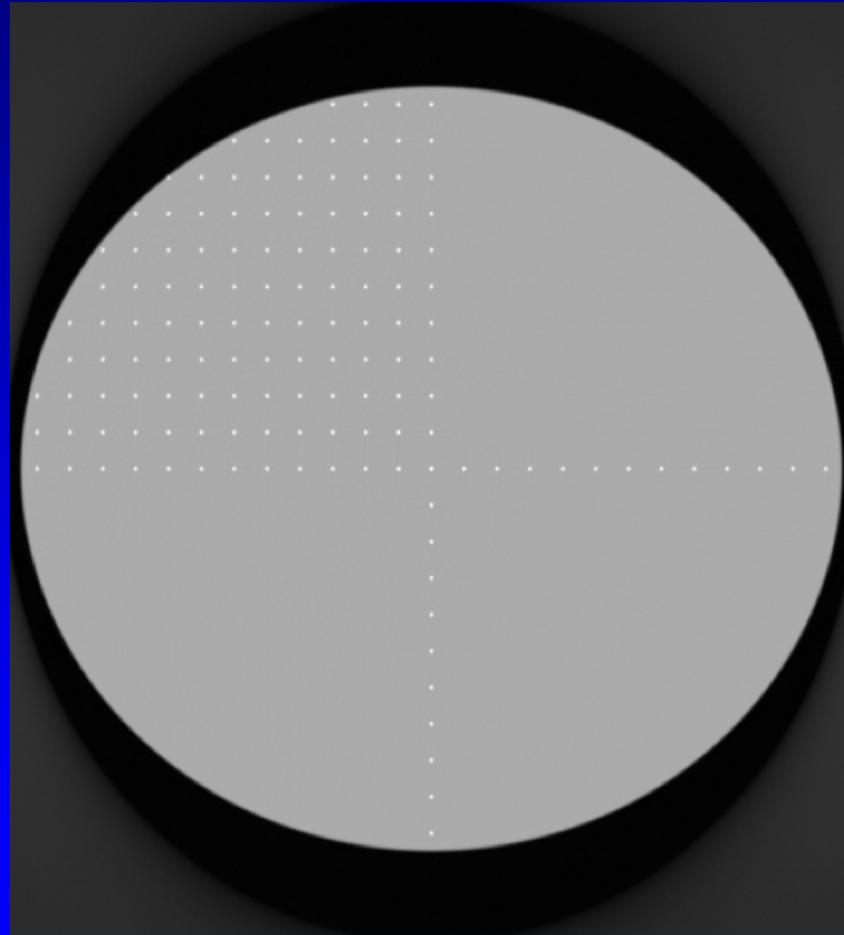
2,-1	1,-1			
	1,0	0,0	1,0	
			1,-1	2,-1

γ

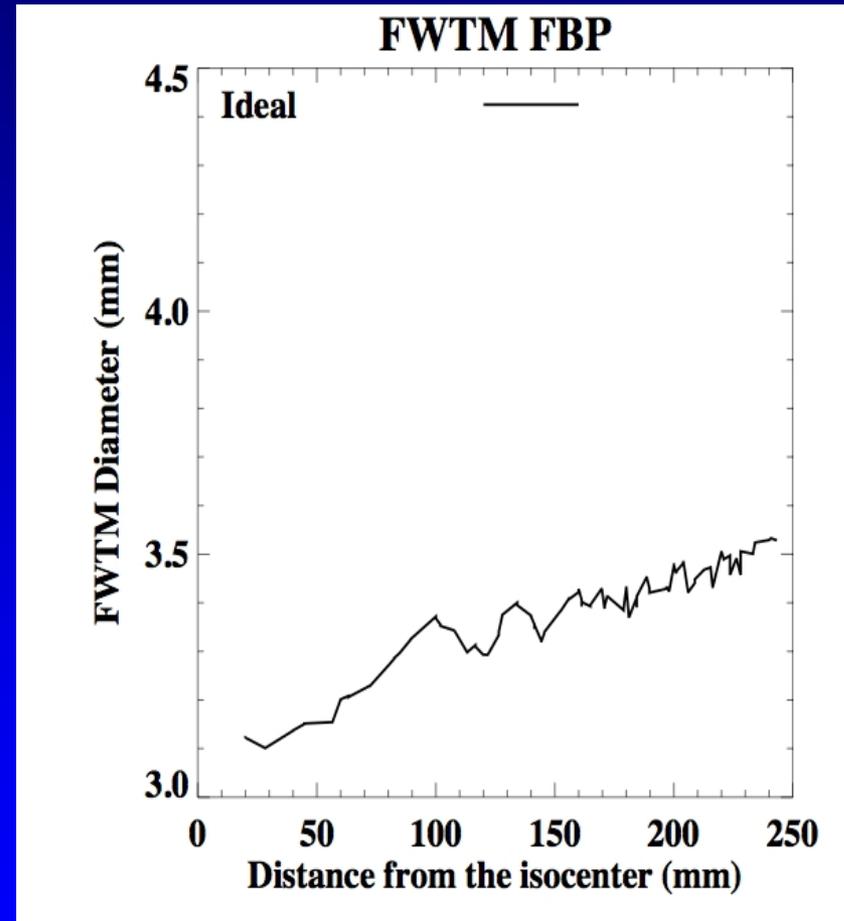
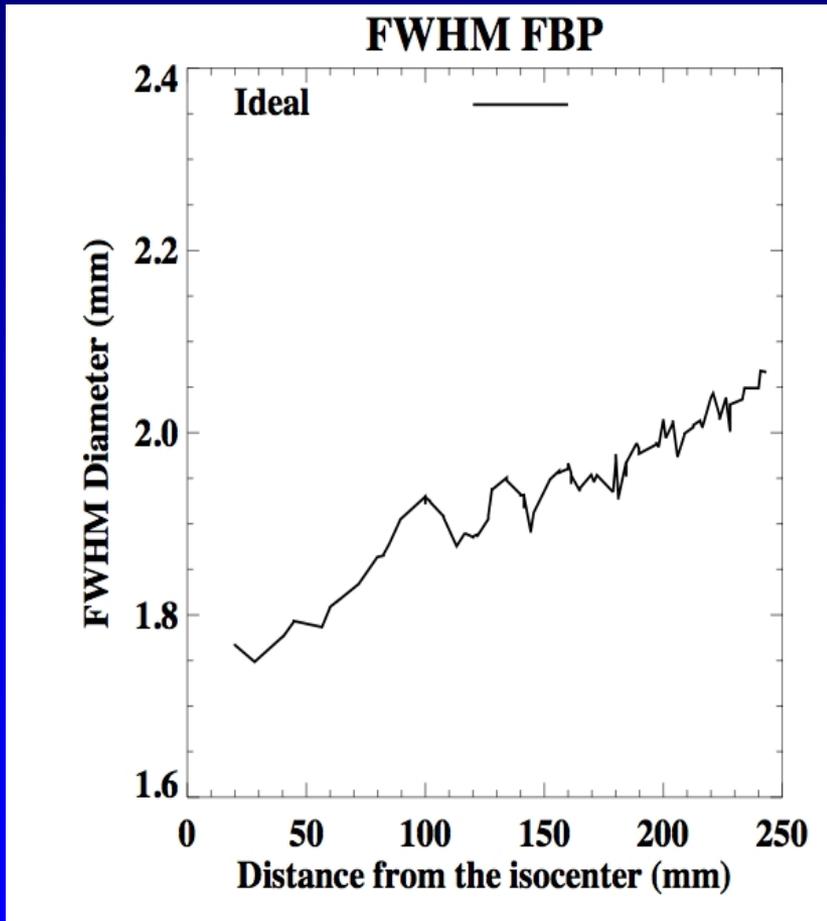


Impulse phantom

- We simulated projections of this phantom in a variety of ways using Radonis package from Philips R&D.
- We then calculated the FWHM and FWTM of the impulses.
- We plot these versus radial distance.

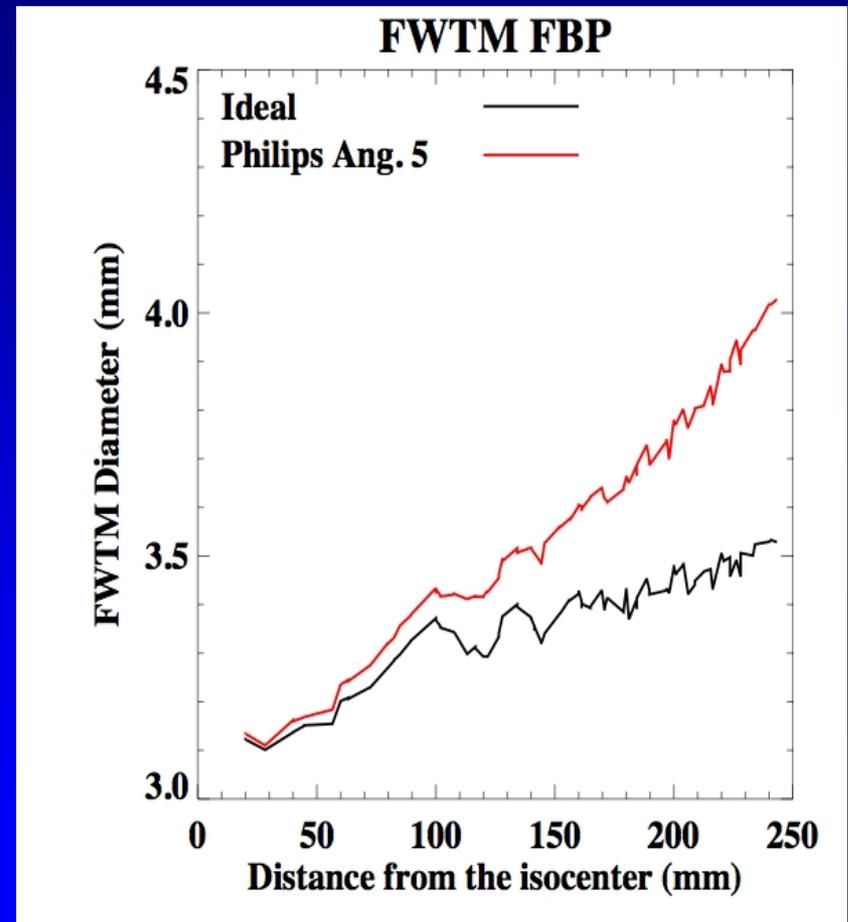
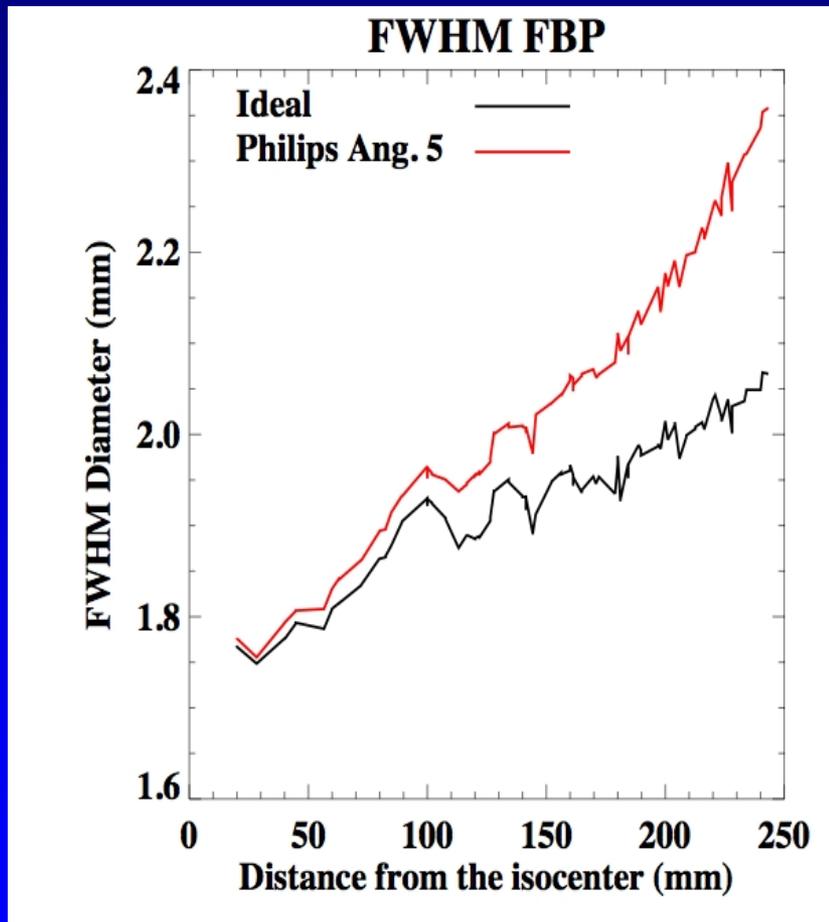


Impulse properties versus distance from isocenter

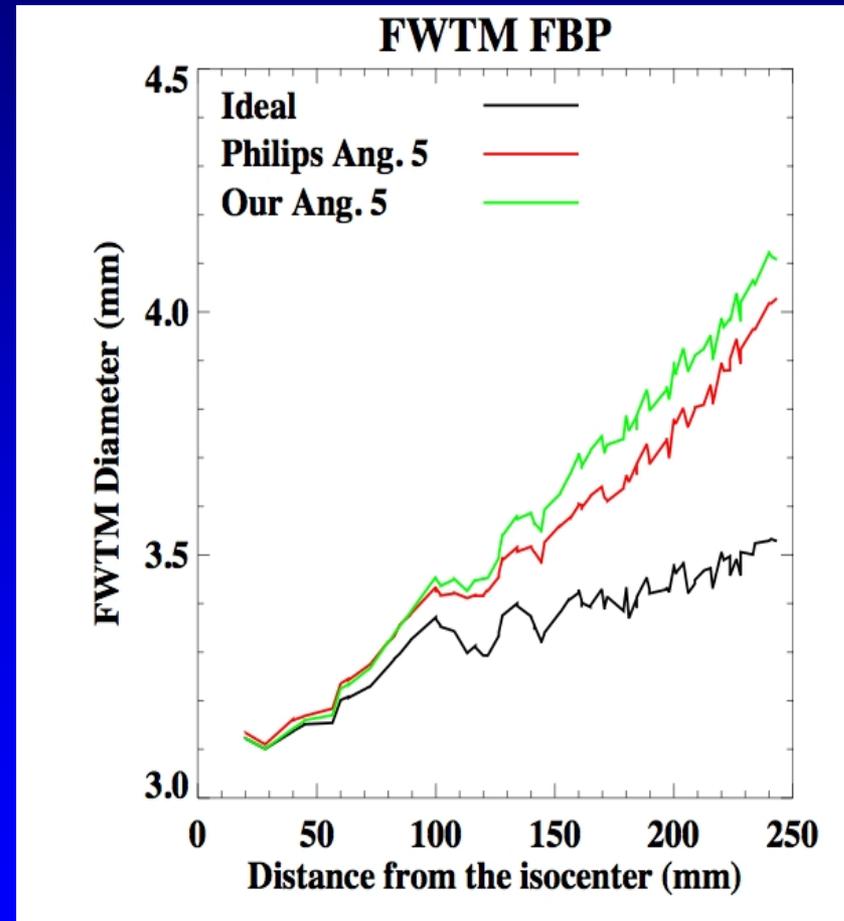
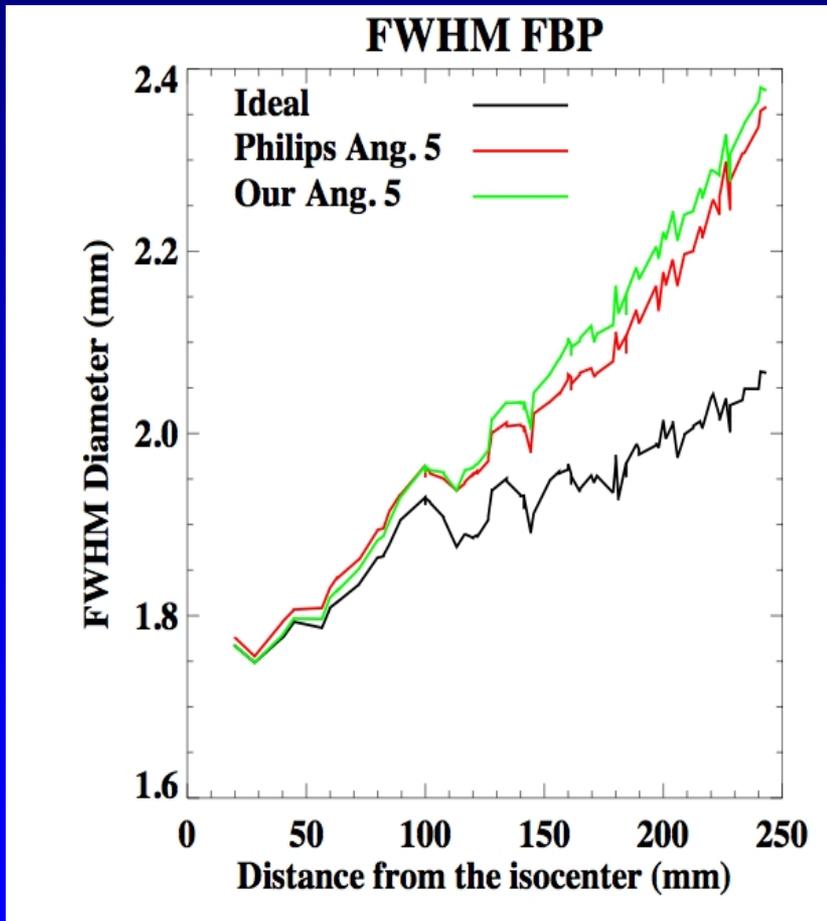


Ideal data is simulated with no focal spot angulation (i.e., 90 degrees).

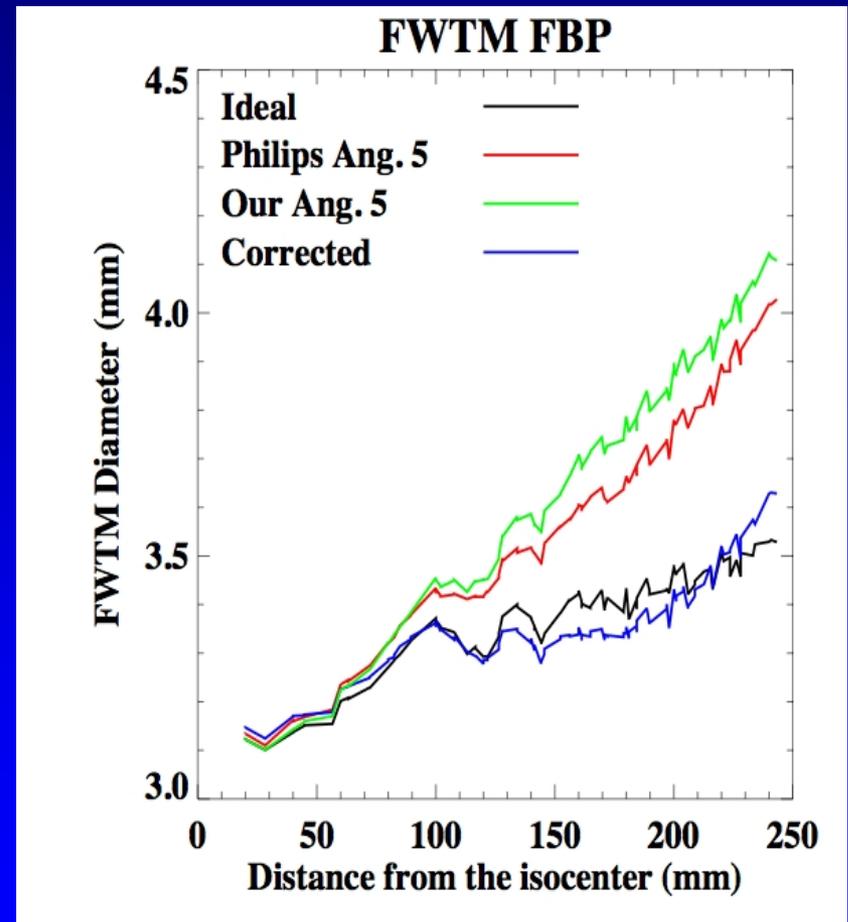
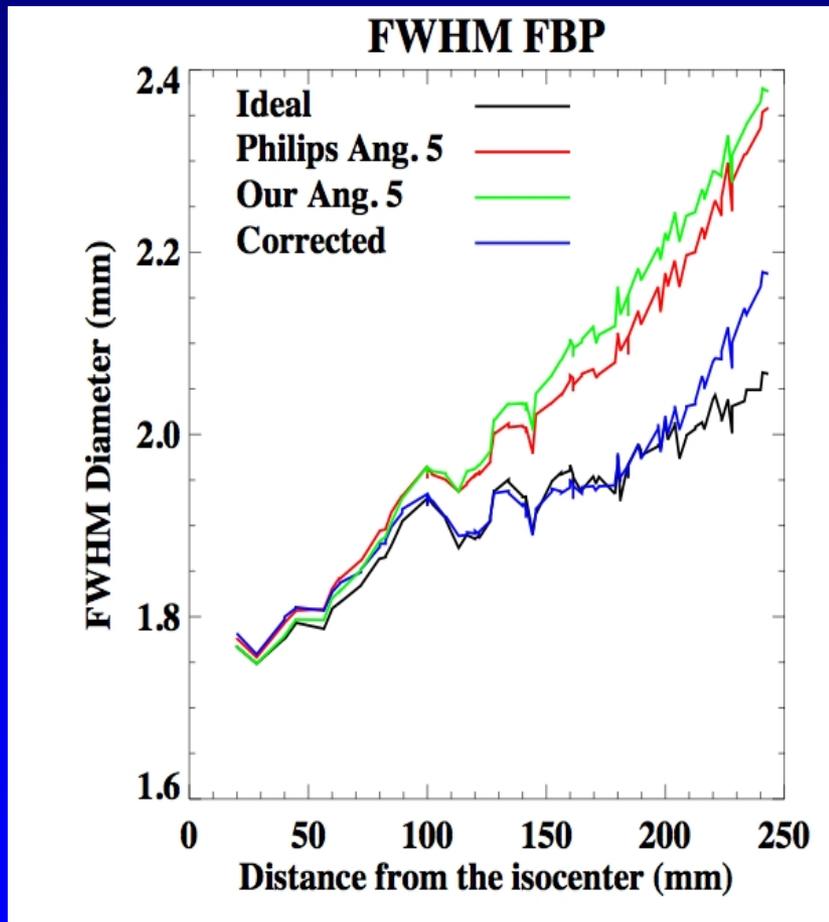
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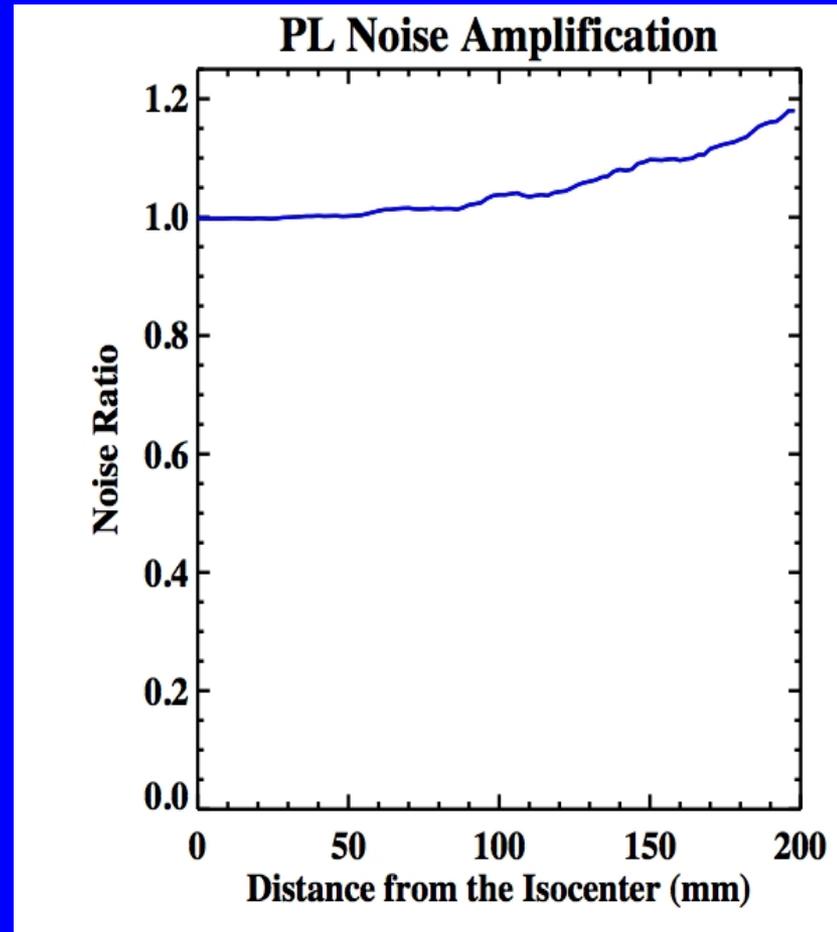
Impulse properties versus distance from isocenter



Impulse properties versus distance from isocenter



In the presence of noise



Comparison to fully iterative methods

Typical
noisy
images

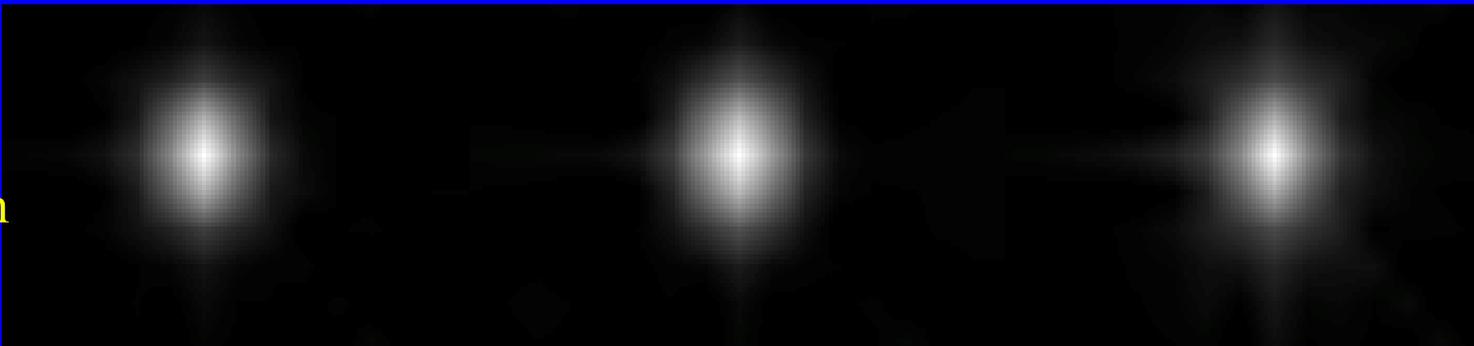


Image domain

Sinogram domain

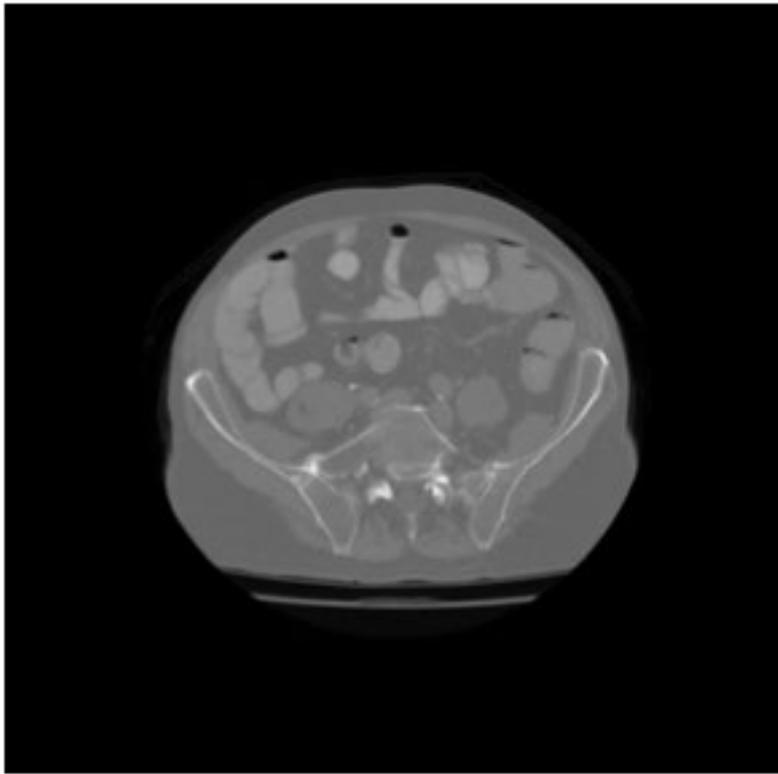
Approx. sino domain

Local
impulse
response in
hot circle

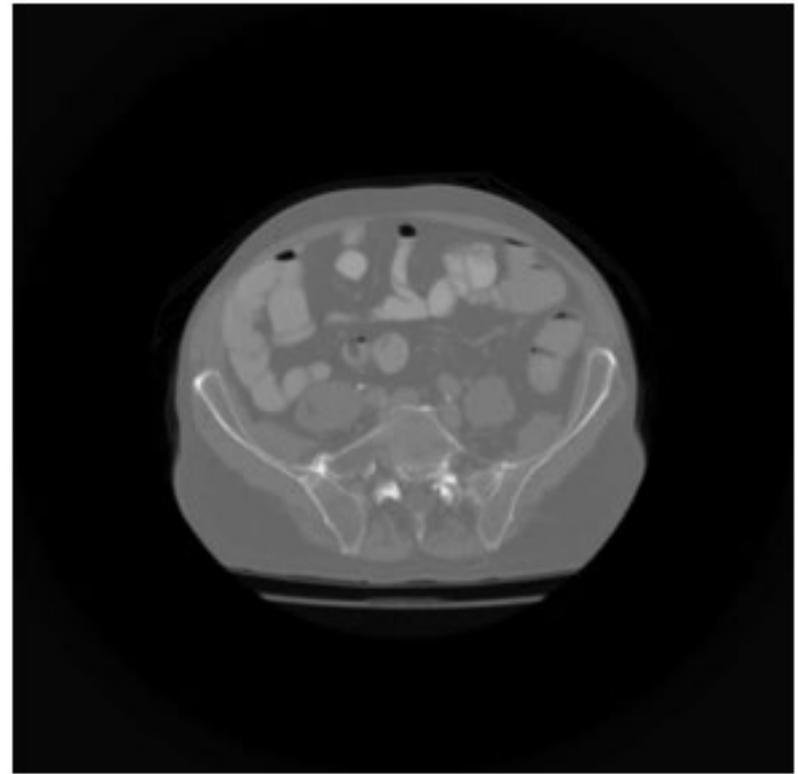


We used closed-form expressions for the PWLS methods to calculate noisy images, local impulse response functions, and variance maps for the three approaches for a $128^2 \times 128^2$ matrix P . We used strip integrals to calculate the forward-projected data and FBP in place of an explicit P^{-1} .

Comparison to fully iterative methods

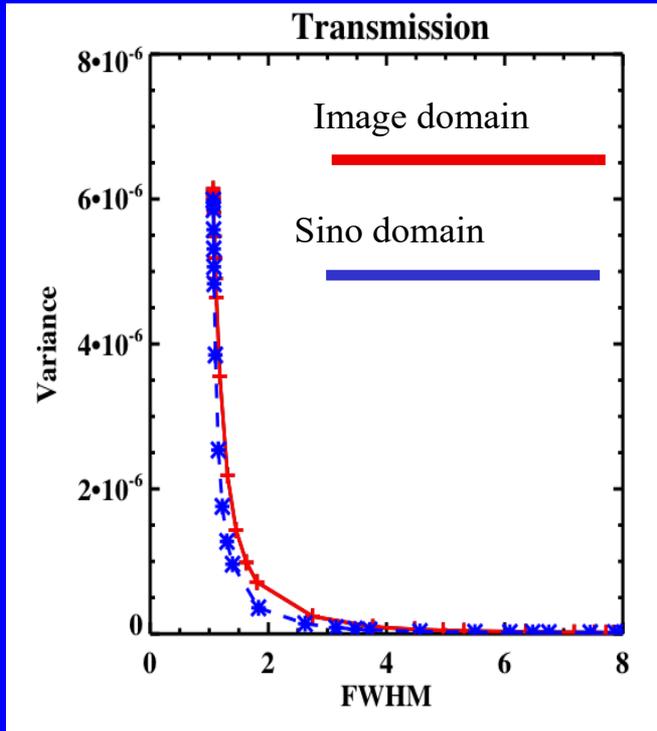


(c) Image-domain



(d) Sinogram-domain

Comparison to fully iterative methods



- Through careful “penalty matching” resolution-variance performance can be very similar.
- Computation is about 100 times faster for sinogram domain.

Limitations:

- Can't easily enforce image-domain non-negativity in sinogram space.
- Can't easily enforce image-domain edge-preserving priors in sinogram space.

Conclusions

- Sinogram restoration is a statistically principled way of preprocessing CT data prior to reconstruction by analytic algorithms
- It can not only be used to reduce artifacts (the point of most preprocessing) but also to reduce noise and model geometric effects, as in fully iterative algorithms.
- At the very least, it represents a computationally efficient middle ground between analytic algorithms and fully iterative ones.
 - ◆ However, in many studies we have done it performs as well as fully iterative algorithms.
 - ◆ It can readily accommodate the proper “nonlinear” model for CT. Many/Most fully iterative algorithms work with linearized system models.
- Naturally it has limitations: harder to accommodate non-negativity and other constraints, harder to implement edge-preserving priors.