CT NOISE POWER SPECTRUM FOR FILTERED BACKPROJECTION AND ITERATIVE RECONSTRUCTION

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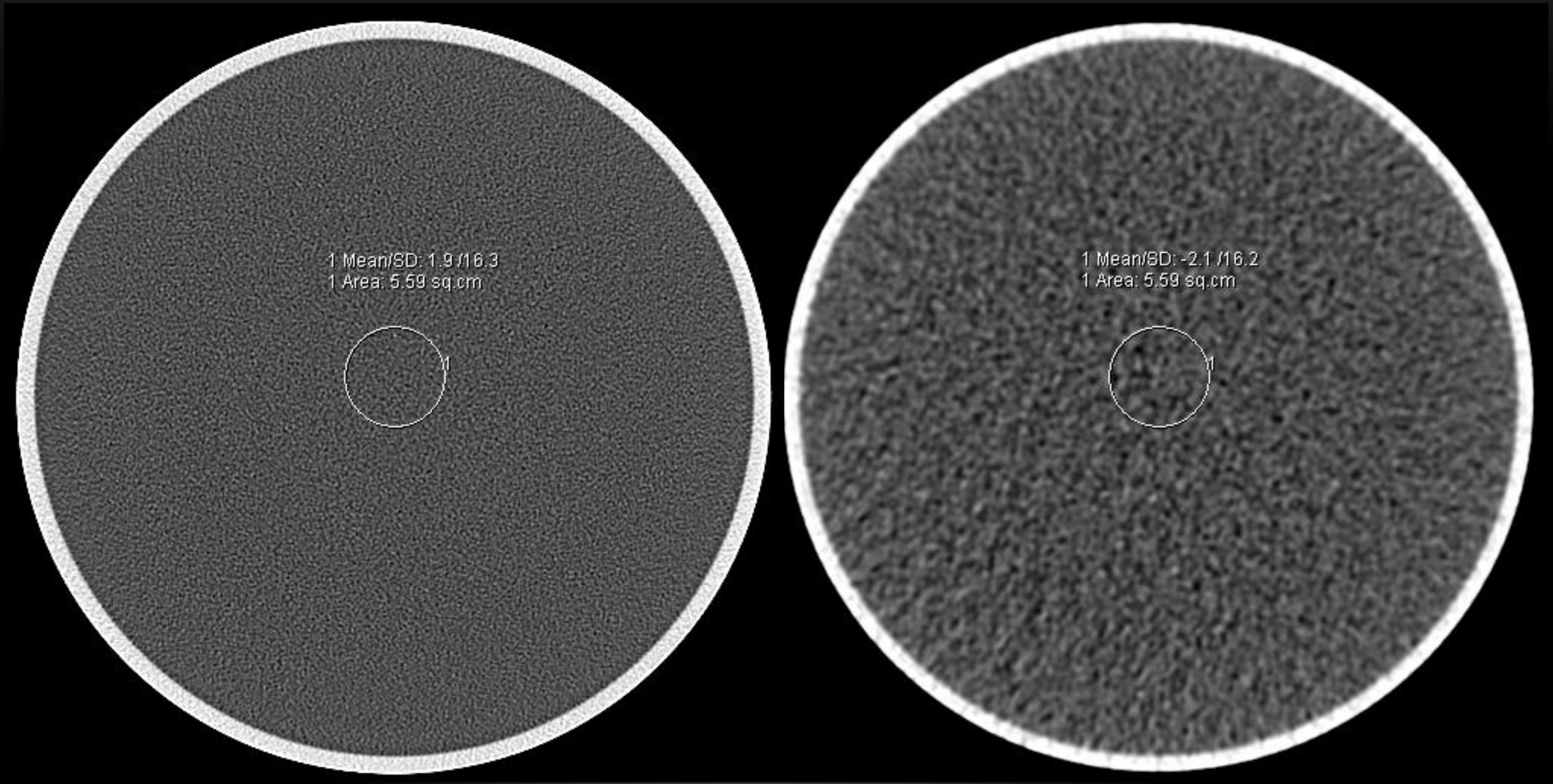
Objectives

- Understand why Noise Power Spectrum(NPS) is a more comprehensive descriptor of CT image noise properties
- Be familiar with methods of evaluating NPS
- Understand why the NPS of Filtered Backprojection (FBP) differs from Iterative Reconstruction (IR)
- Be familiar with IR’s noise property and its implication on CT protocol optimization

Same Noise Magnitude but Different Texture



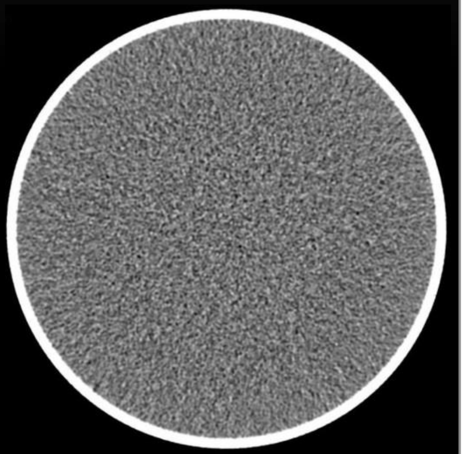
120 kV, 1000 eff mAs, B70
Noise =16

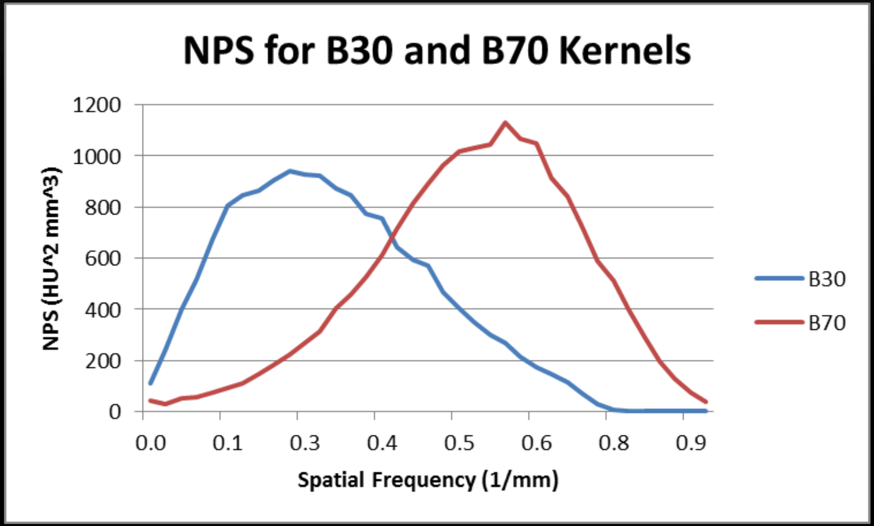
120 kV, 10 eff mAs, B10
Noise =16

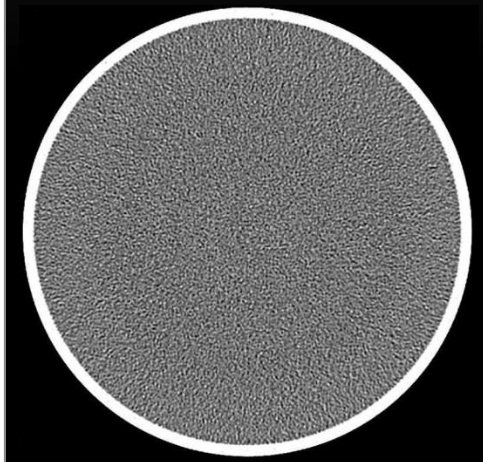
Why Noise Power Spectrum (NPS)?

- Noise (standard deviation) only measures the magnitude of image noise properties.
- Noise power spectrum measures not only the magnitude but also the spatial correlation of noise properties (“texture”).

NPS for Images w/ Different Noise Texture





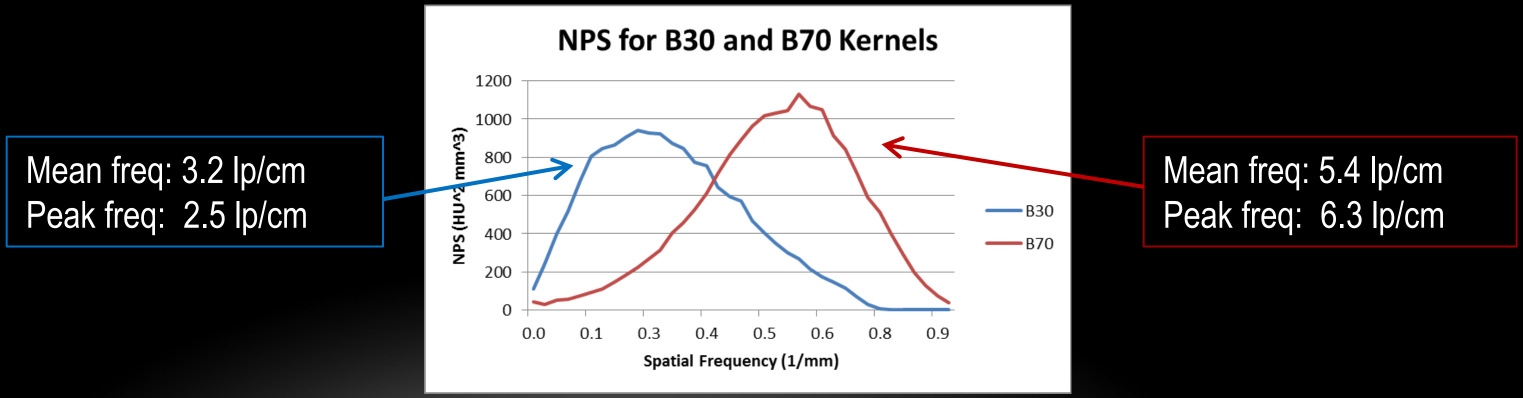


B30

B70

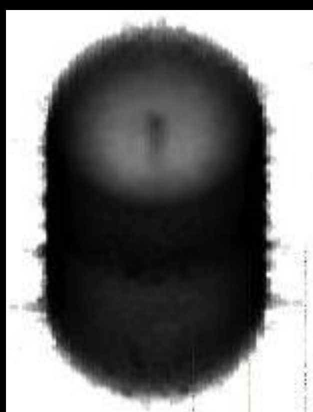
What information can we get from NPS?

- Area under NPS curve is equal to the square of noise (magnitude)
- Mean and peak frequencies are related to the noise texture (“ noise grain size”).
- Fine texture usually indicates NPS has higher mean and peak frequencies

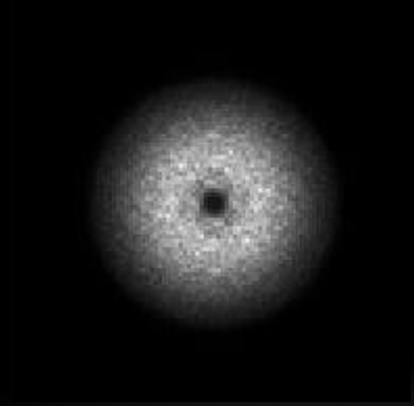


Evaluating CT Noise Power Spectrum

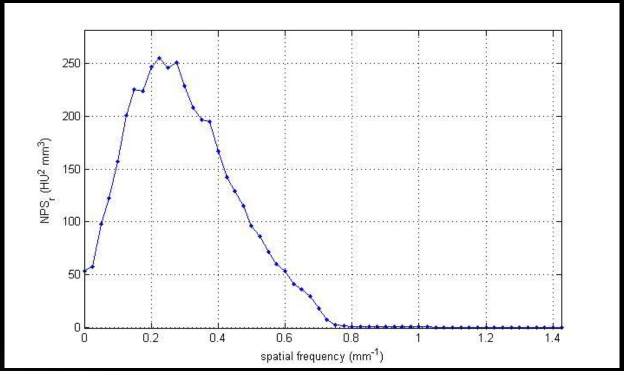
- NPS is determined from the Fourier transform of the spatial autocorrelation function of a zero-mean noise image.
- For CT volumetric image data, NPS can be evaluated in 3D, 2D, or 1D (radially-averaged 2D)



3D



2D (xy-plane)



1D (radially-averaged 2D)

Equations for NPS Evaluation

3D NPS: $\mathrm{NPS}_{3D}(f_x, f_y, f_z) = \frac{\Delta x \Delta y \Delta z}{N_x N_y N_z} < \left| DFT_{3D}\{I(x,y,z) - \overline{I(x,y,z)}\}\right|^2 >$

2D NPS $f_x f_y$-plane: $\mathrm{NPS}_{2D}(f_x, f_y) = \frac{\Delta x \Delta y}{N_x N_y} < \left| DFT_{2D}\{I(x,y) - \overline{I(x,y)}\}\right|^2 >$

2D NPS $f_y f_z$-plane: $\mathrm{NPS}_{2D}(f_y, f_z) = \frac{\Delta y \Delta z}{N_y N_z} < \left| DFT_{2D}\{I(y,z) - \overline{I(y,z)}\}\right|^2 >$

- $I(x,y,z)$ is the CT volumetric image data, and $\overline{I(x,y,z)}$ is the averaged image to remove the DC components and/or de-trending
- $\langle \ldots \rangle$ is the ensemble mean
- 1D NPS is computed through radially-average of 2D NPS.

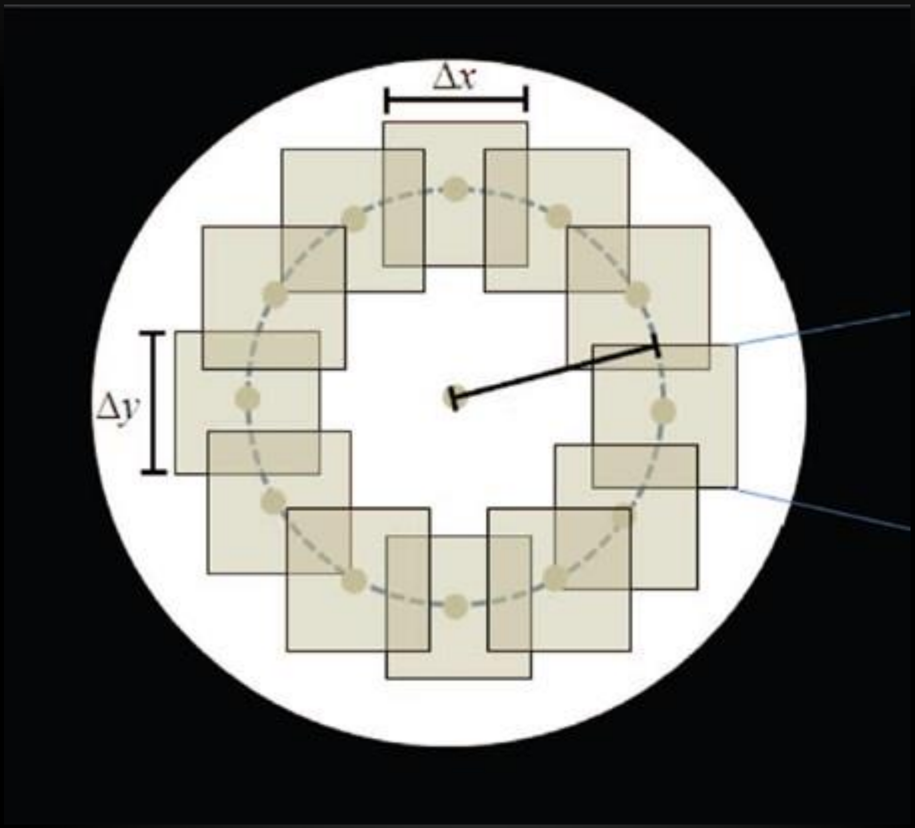
Siewerdsen et al, "A framework for noise-power spectrum analysis of multidimensional Images" Medical Physics, Vol. 29, No. 11, November 2002

De-trend CT Images

To de-trend and remove structured noise:

- By subtracting a polynomial fitted (2^{nd} order) image from the original.
- For repeated acquisitions, use the difference image from two adjacent scans.
  - The NPS computed from the difference image should be divided by 2
  - To have the better de-trended image, make sure the tube starting angle is the same for the adjacent scans.

NPS Estimate Based on Single Acquisition



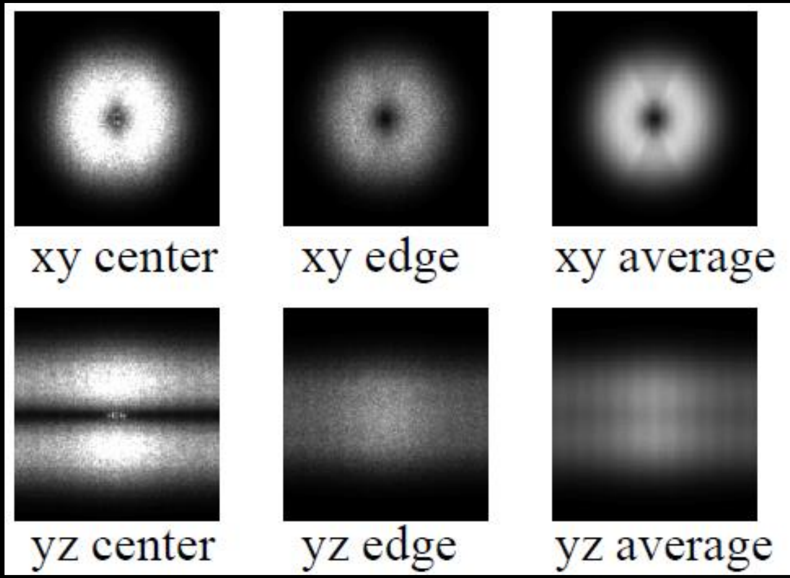
ROIs distributed radial-symmetrically

NPS Evaluation via Repeat Acquisitions

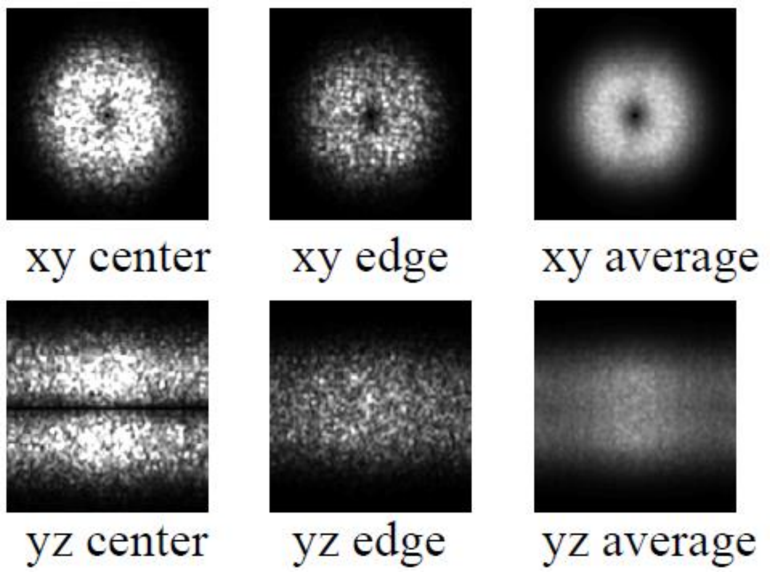
- For repeat acquisitions, the ensemble mean of NPS can be computed from images from repeat scans.
- The ensemble mean NPS tends to be less noisy for better estimate of mean and peak frequencies.

Ensemble Mean NPS of Repeated Scans

- NPS via ensemble mean of repeat acquisitions has smoother appearance than those from the single acquisition.



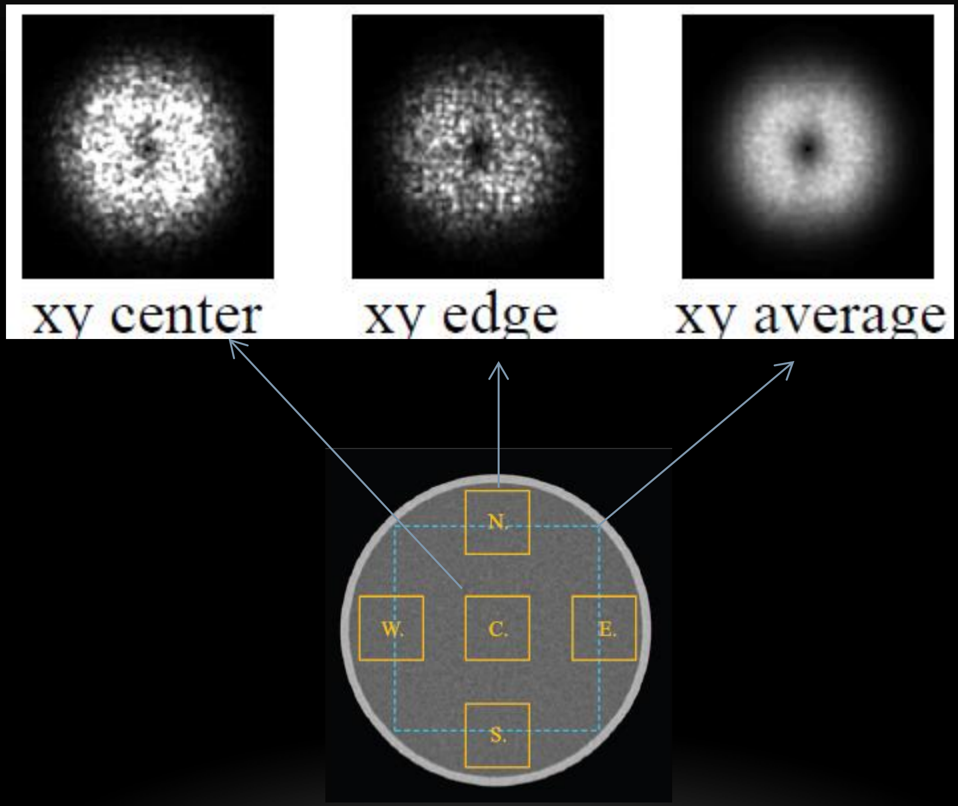
Ensemble mean via repeat scans



NPS via single scan

Yu et al, “Measurement and analysis of 3D NPS of an iterative reconstruction method in CT” RSNA 2012

Location-dependency of noise pattern



Yu et al, “Measurement and analysis of 3D NPS of an iterative reconstruction method in CT” RSNA 2012

Inter-vendor Comparison of Recon Kernels

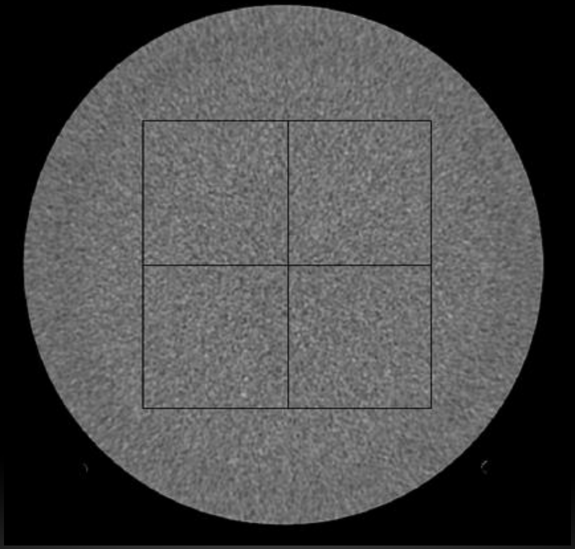
For a CT site with more than one CT vendor, it is difficult to find matching recon kernels:

- GE: soft, standard, detail, chest, lung, bone, bone+, edge
- Siemens: B10f, B20f, B22f, B23f, B26f, B30f, B31f, B35f… B80f.
- Solomon et al. used similarity of the NPS to compare CT recon kernels between GE and Siemens

Solomon et al, “Quantitative Comparison of Noise Texture Across CT Scanners” Medical Physics, Vol. 39, No. 10, October 2012

Phantom and ROI Placement

- Using module 3 (uniform section) of the ACR CT phantom
- Four ROIs in each slice and multiple slices in each acquisition



Solomon et al, “Quantitative Comparison of Noise Texture Across CT Scanners” Medical Physics, Vol. 39, No. 10, October 2012

NPS Comparison Steps

- Normalizing the 1D NPS by its integrated area -> nNPS
- Filtering nNPS with a human visual response function
- Root Mean Square Difference (RMSD) and Peak Frequency Difference (PFD) of NPSs as the metrics of similarity

Solomon et al, “Quantitative Comparison of Noise Texture Across CT Scanners” Medical Physics, Vol. 39, No. 10, October 2012

Human Visual Response Function

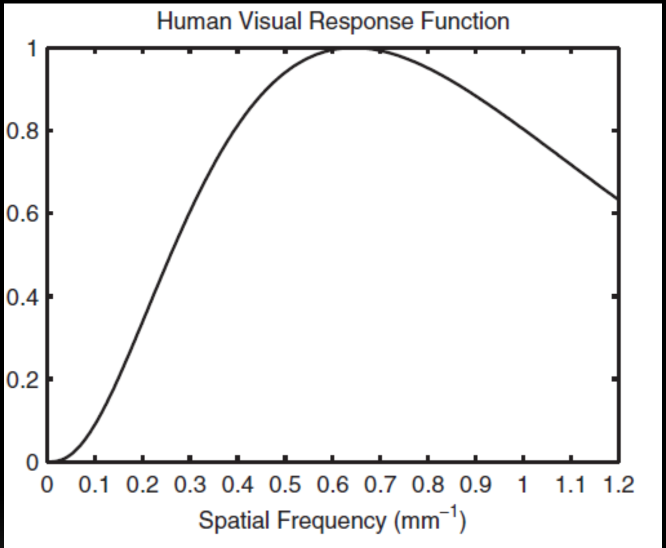
- Human visual response function is used to account for the variable perception of noise by human at different spatial frequencies

$$\mathrm{nNPS}_f(r) = \mathrm{nNPS}(r) \cdot |V(\rho)|^2,$$

$$\rho = f \cdot \frac{\mathrm{FOV} \cdot R \cdot \pi}{D \cdot 180},$$

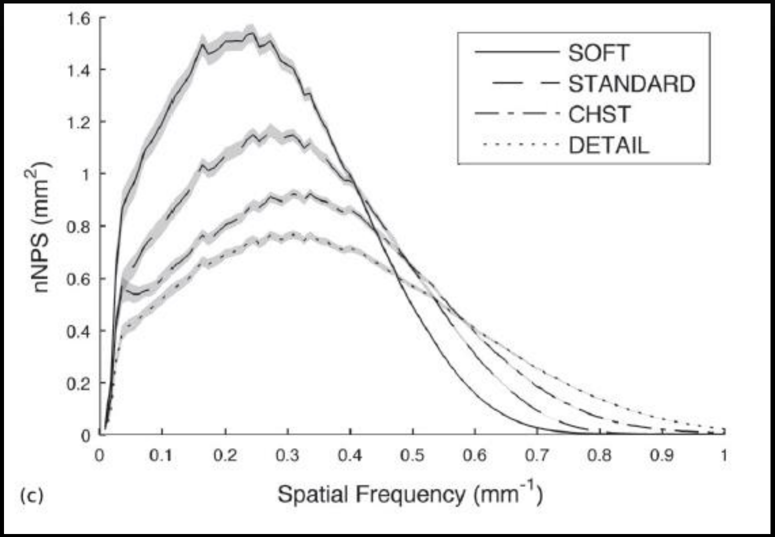
$$V(\rho) = |\eta \rho^{a_1} \cdot e^{-a_2 \rho^{a_3}}|^2,$$

$nNPS_f$(r) is normalized NPS by its area,
V(ρ) is the human visual response function

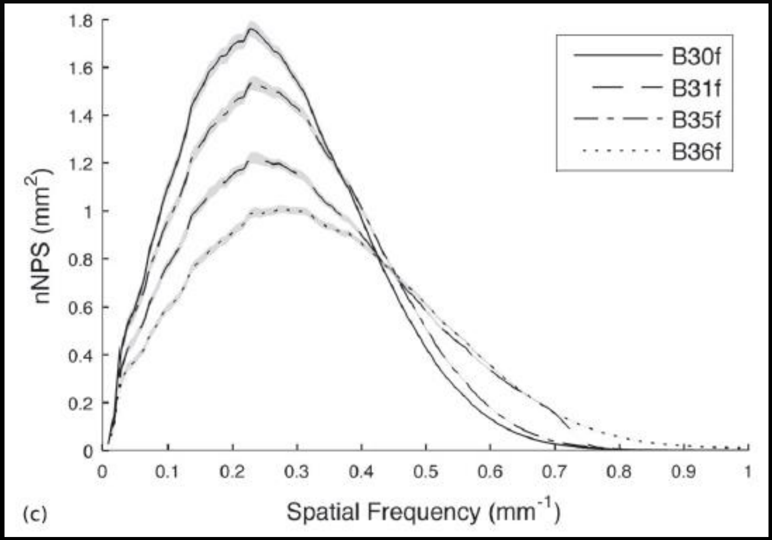


Solomon et al, "Quantitative Comparison of Noise Texture Across CT Scanners" Medical Physics, Vol. 39, No. 10, October 2012

Normalized NPS



Normalized NPS for GE recon kernels



Normalized NPS for Siemens recon kernels

Solomon et al, "Quantitative Comparison of Noise Texture Across CT Scanners" Medical Physics, Vol. 39, No. 10, October 2012

Relative Noise and Peak Frequencies

TABLE II. Relative noise magnitude (normalized by the standard kernel) and peak frequencies of the $nNPS_f(r)$ curves for GE kernels.

Kernel	Relative noise	Peak frequency (mm^{-1})
Soft	0.81	0.39
Standard	1.00	0.43
Detail	1.23	0.48
Chest	1.23	0.46
Lung	4.01	0.55
Bone	3.38	0.75
Bone+	5.07	0.74
Edge	6.39	1.03

Relative noise and peak frequencies for GE recon kernels

TABLE III. Relative noise magnitude (normalized by the B43f kernel) and peak frequencies of the $nNPS_f(r)$ curves for Siemens kernels.

Kernel	Relative noise	Peak frequency (mm^{-1})	Kernel	Relative noise	Peak frequency (mm^{-1})
B10f	0.44	0.29	B41f	0.86	0.44
B20f	0.56	0.33	B43f	1.00	0.43
B22f	0.62	0.37	B45f	1.26	0.45
B23f	0.62	0.37	B46f	1.18	0.49
B26f	0.57	0.36	B50f	1.93	0.52
B30f	0.69	0.37	B60f	3.98	0.62
B31f	0.74	0.42	B70f	4.39	0.61
B35f	0.66	0.39	B75f	3.71	0.62
B36f	0.75	0.44	B80f	4.38	0.55
B40f	0.84	0.40			

Relative noise and peak frequencies for Siemens recon kernels

Solomon et al, "Quantitative Comparison of Noise Texture Across CT Scanners" Medical Physics, Vol. 39, No. 10, October 2012

Closest matched Siemens kernel for a GE kernel

TABLE IV. Closest matching Siemens kernel for a given GE kernel.

GE	Siemens	RMSD (mm^2)	PFD (mm^{-1})
Soft	B35f	0.01	0.00
Standard	B43f	0.01	0.00
Chest	B41f	0.01	0.01
Detail	B46f	0.04	-0.01
Lung	B80f	0.03	0.00
Bone	B75f	0.10	0.13
Bone+	B75f	0.09	0.12
Edge	B75f	0.18	0.41

Solomon et al, “Quantitative Comparison of Noise Texture Across CT Scanners” Medical Physics, Vol. 39, No. 10, October 2012

Noise Texture Comparison for Matching Kernels

Solomon et al, “Quantitative Comparison of Noise Texture Across CT Scanners” Medical Physics, Vol. 39, No. 10, October 2012

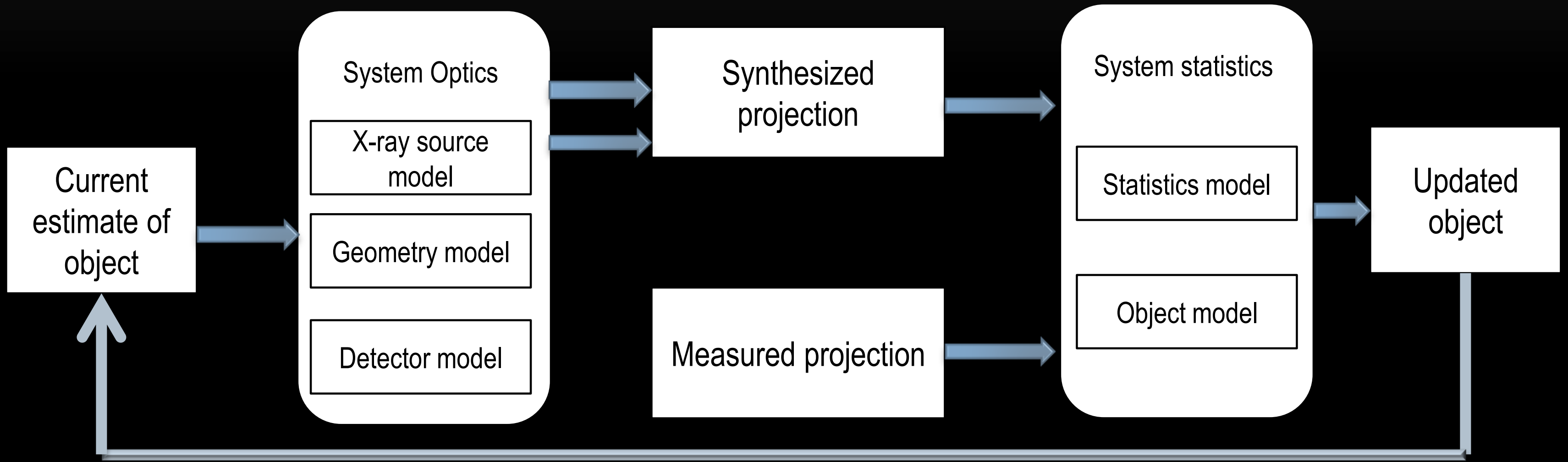
CT Iterative Reconstruction

- Is a feature that uses the information acquired during the scan and repeated reconstruction steps to produce an image with less “noise” or better image quality (e.g., higher spatial resolution or decreased artifacts) than is achievable using standard reconstruction techniques (FBP)

CT Iterative Reconstruction

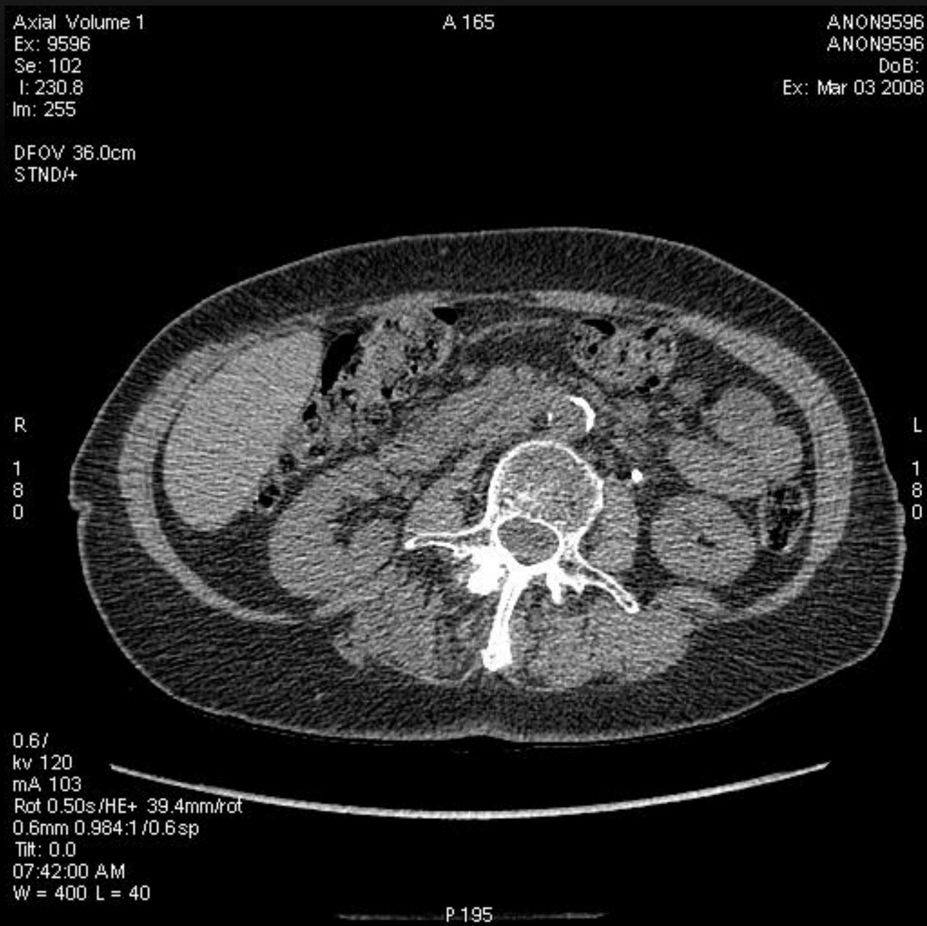
- Iterative Reconstruction may be completed using data in Image Space, Projection (raw CT data) or a Model Based Approach. Projection or Model based approach is much better implementation but increases recon time.

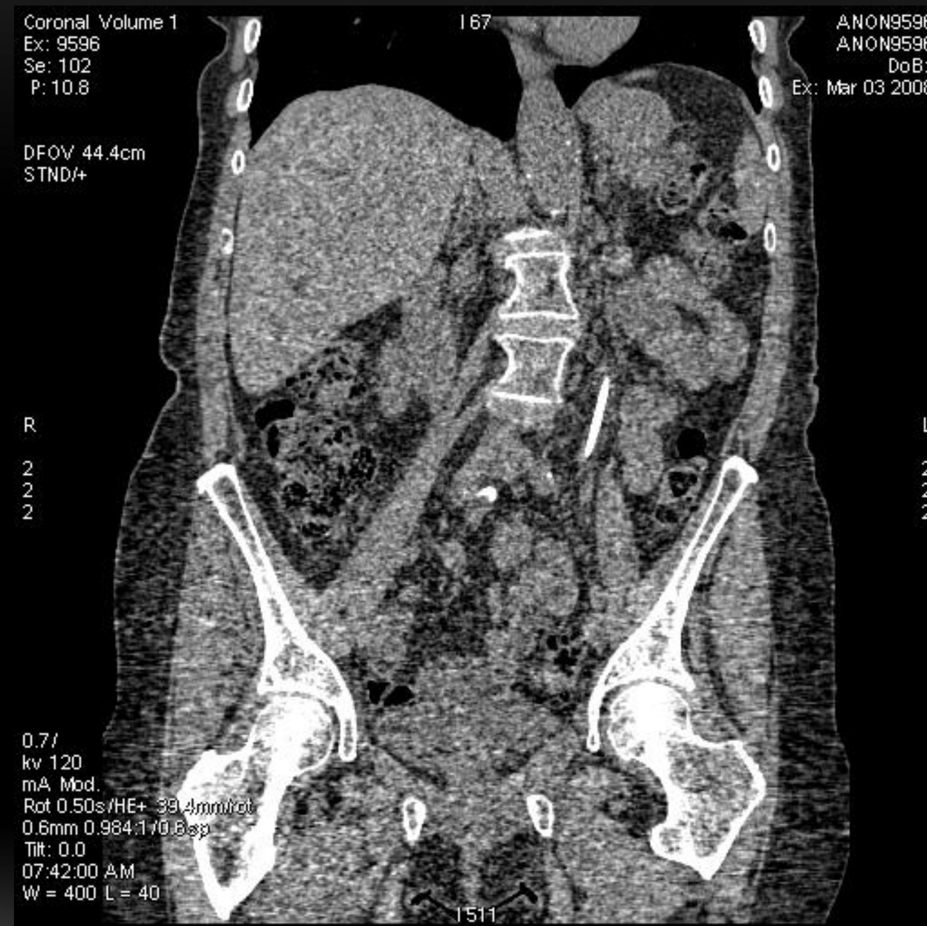
Model-based Iterative Reconstruction



Repeat the loop until measured and synthesized projections converge

Standard FBP Images

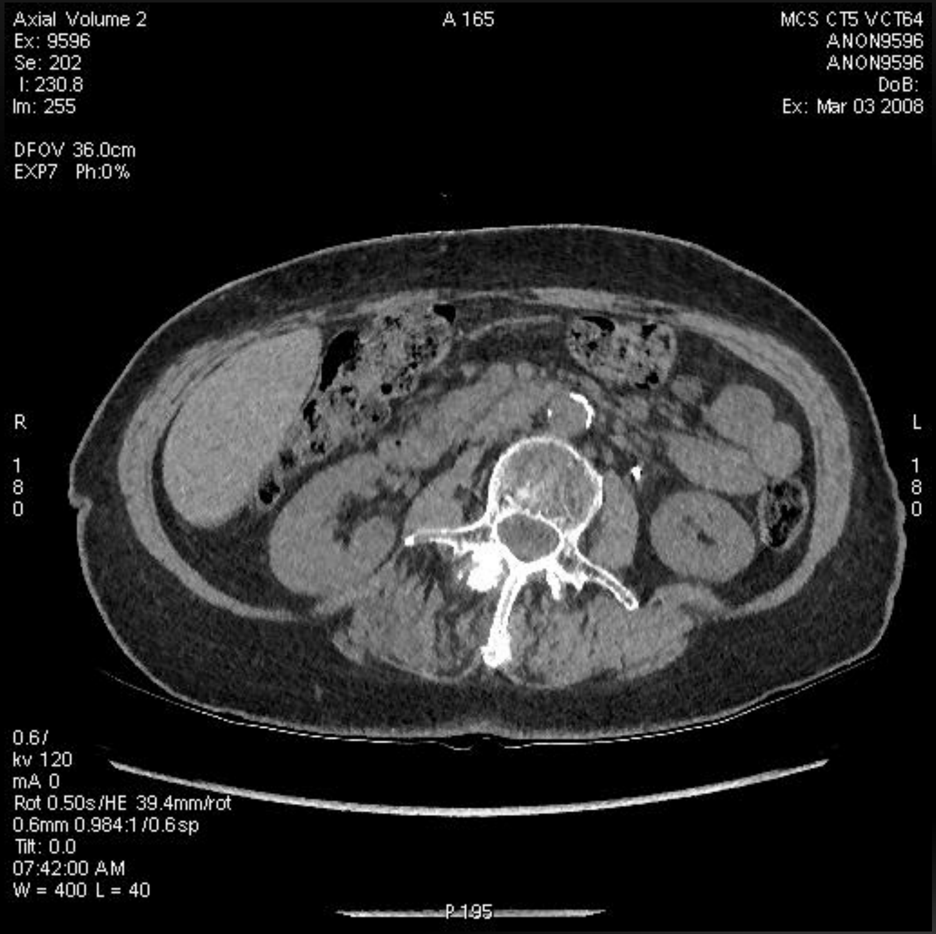


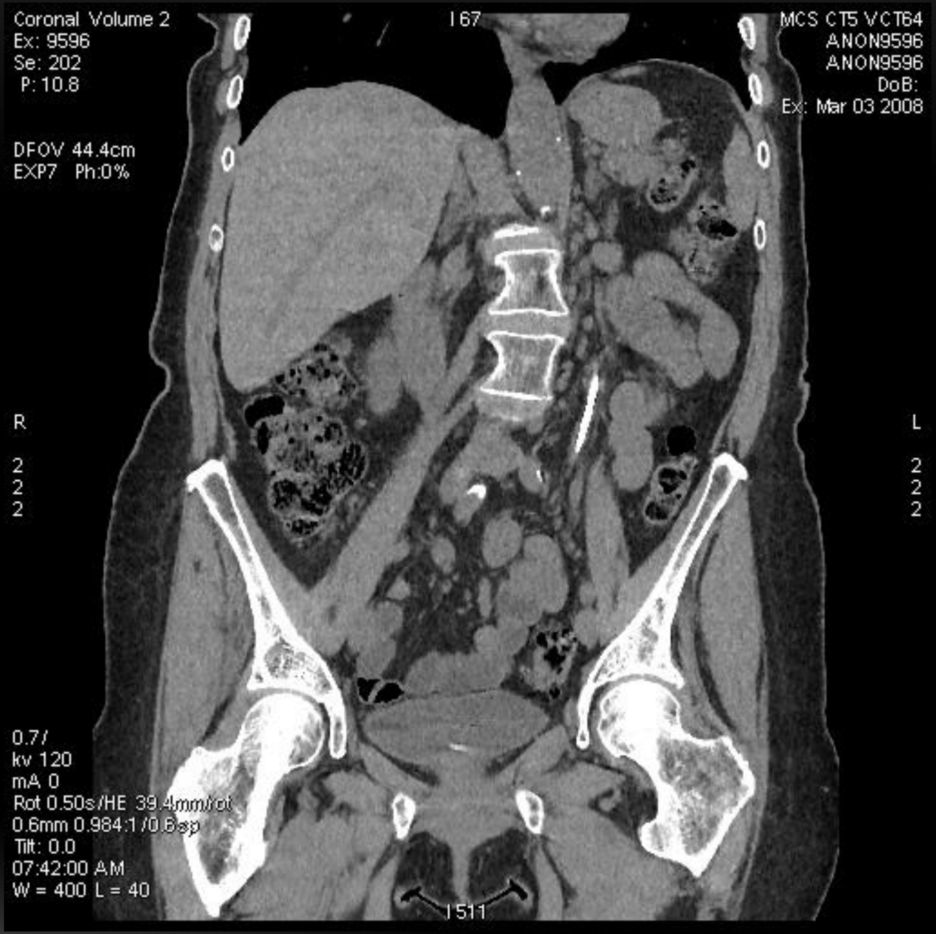


Axial Image CTDIvol =3.7mGy Coronal MPR

Images courtesy of GE Healthcare

Model Based Iterative Recon (Veo) Images





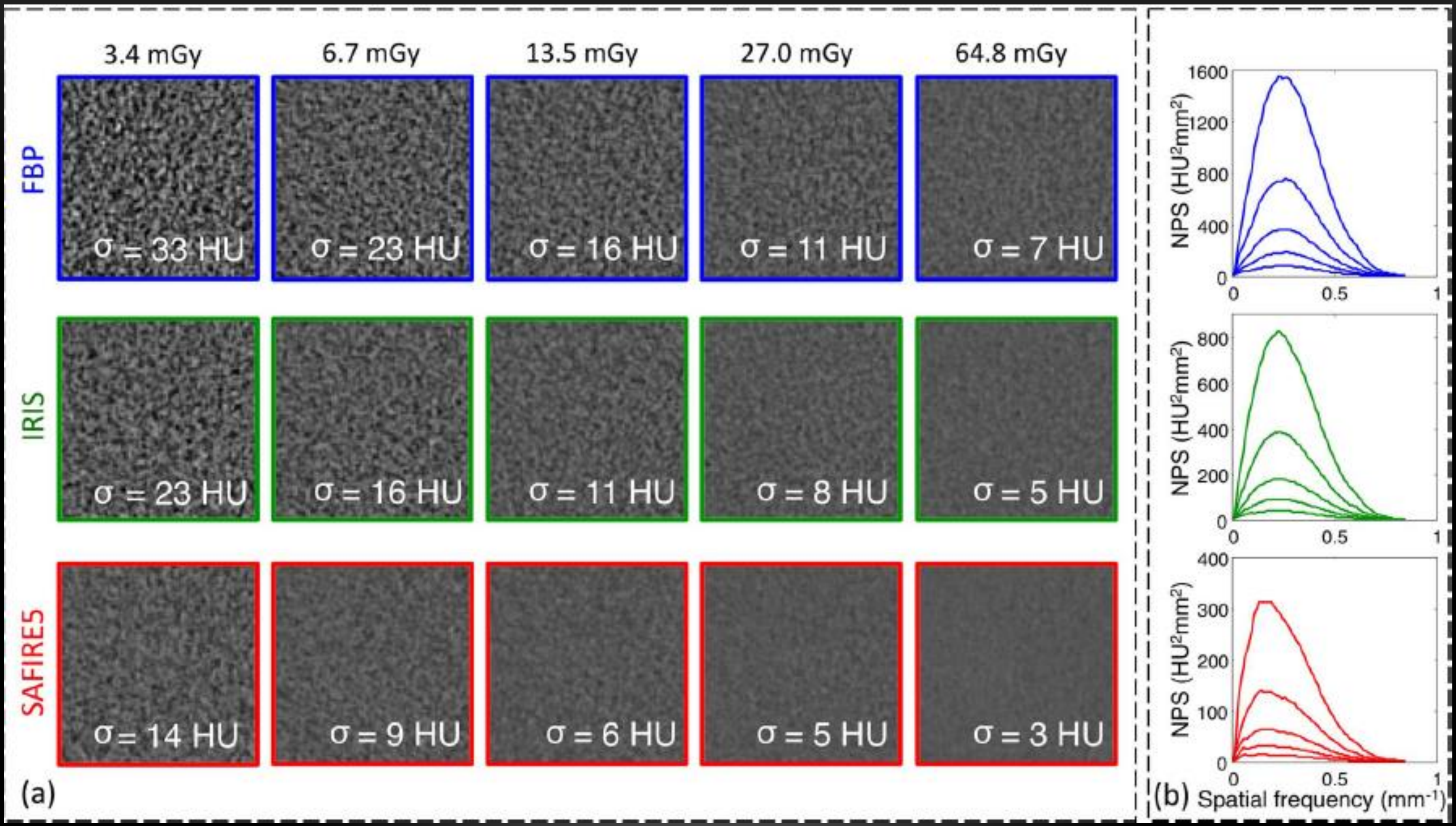
Axial Image CTDIvol =3.7mGy Coronal MPR

Images courtesy of GE Healthcare

Nonlinear Statistics Model in IR

- In the statistics model of IR algorithm, there is an adaptive regularization term which depends on local contrast gradient, i.e., it can reduce the noise in homogeneous regions and preserve details at edges.
- The nonlinear regularization term may be more aggressive for noisier data.

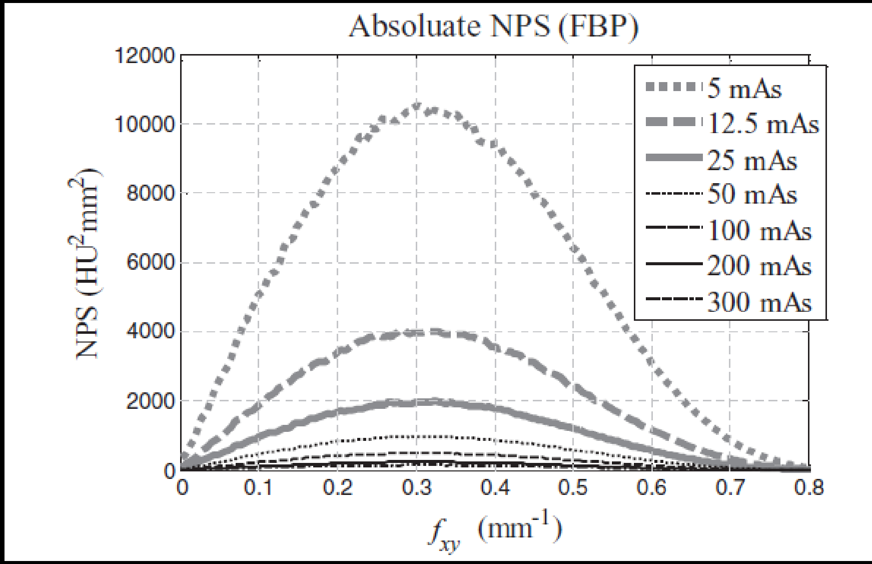
Noise Comparison between FBP and IR



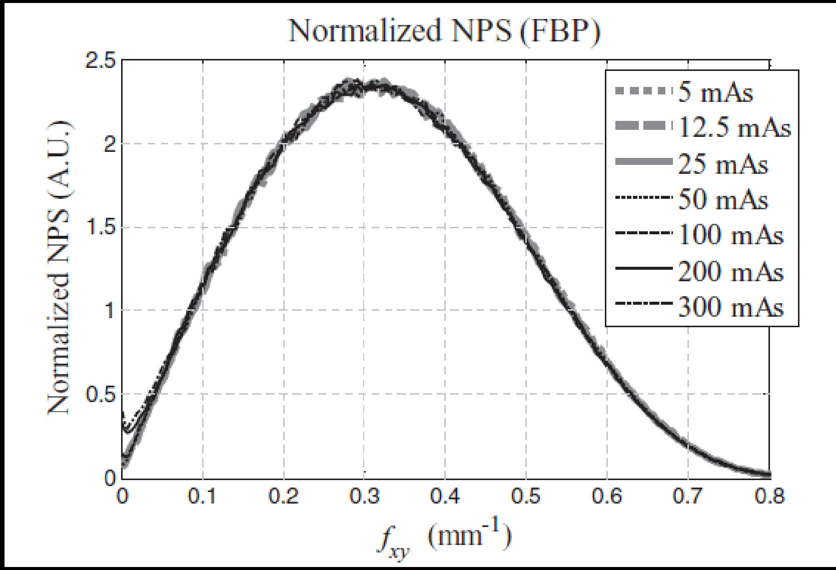
Chen et al, "Assessing CT Noise and Resolution for Nonlinear Reconstruction" Medical Physics, Vol. 41, No. 7, July 2014

FBP: NPS vs. Dose

- The shape of normalized NPS is similar at different dose levels for FBP images



NPS at different dose levels

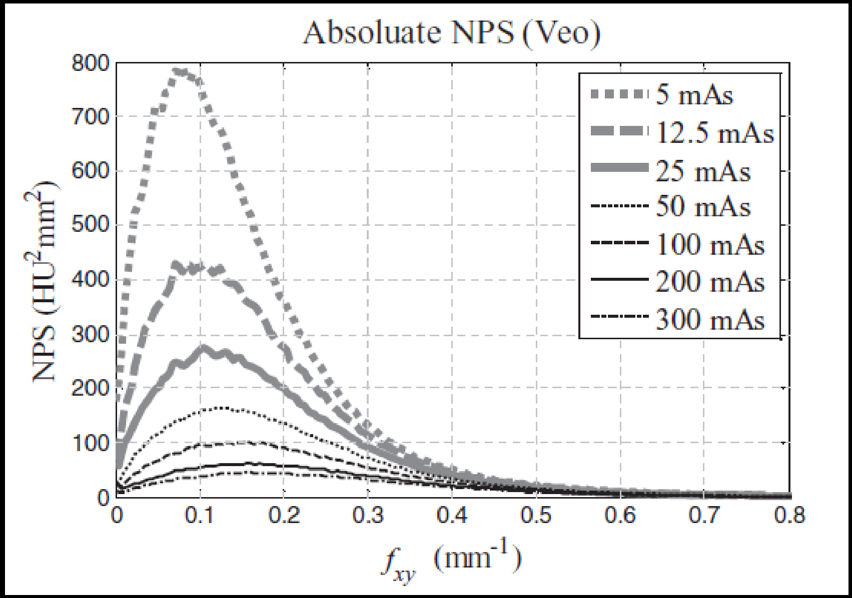


NPS normalized

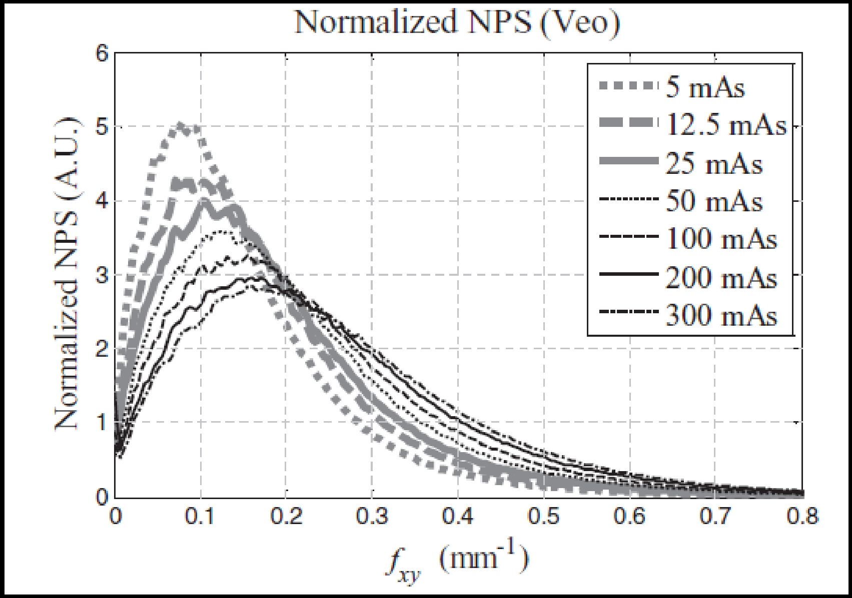
Li et al, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance" Medical Physics, Vol. 41, No. 4, April 2014

IR: NPS vs. Dose

- The shape of normalized NPS is not similar at different dose levels for IR images



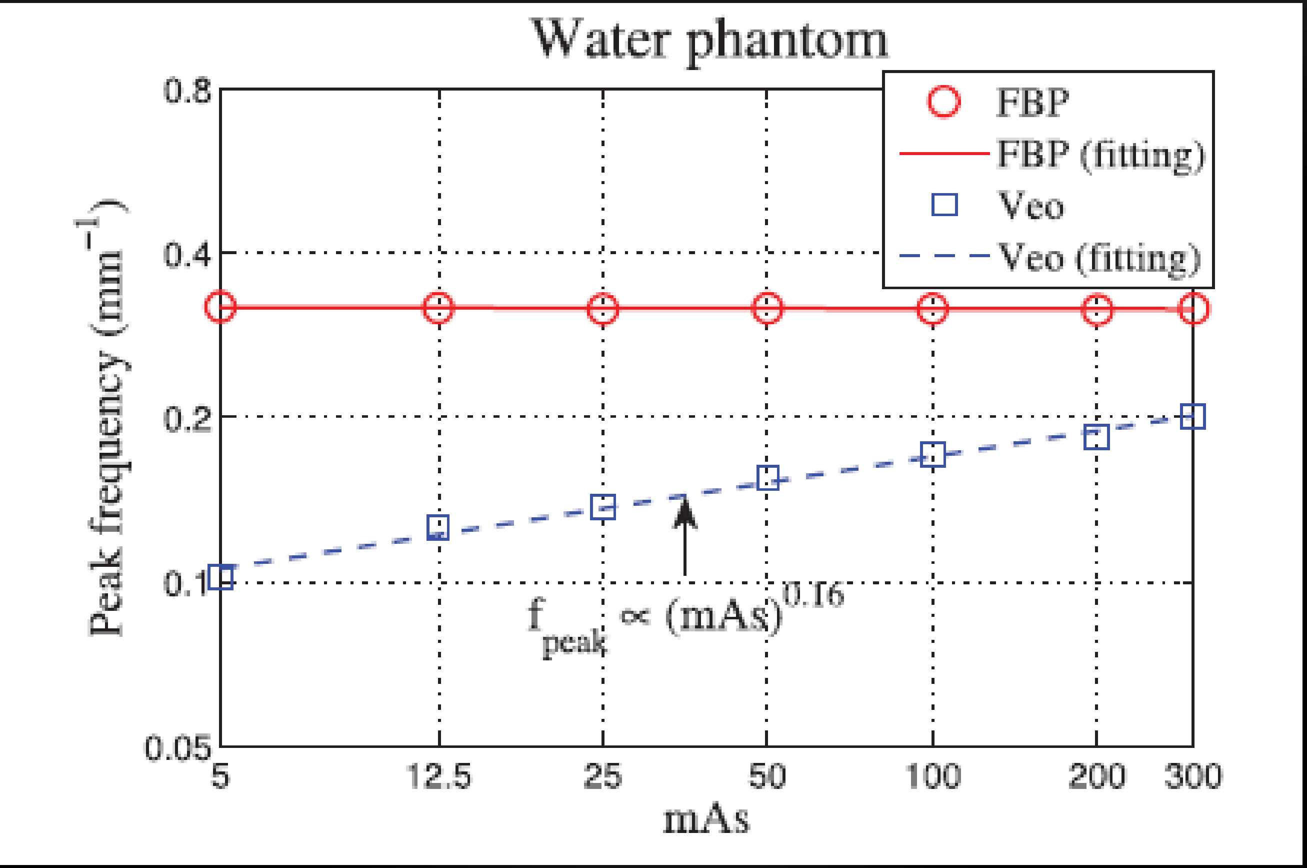
NPS at different dose levels



NPS normalized

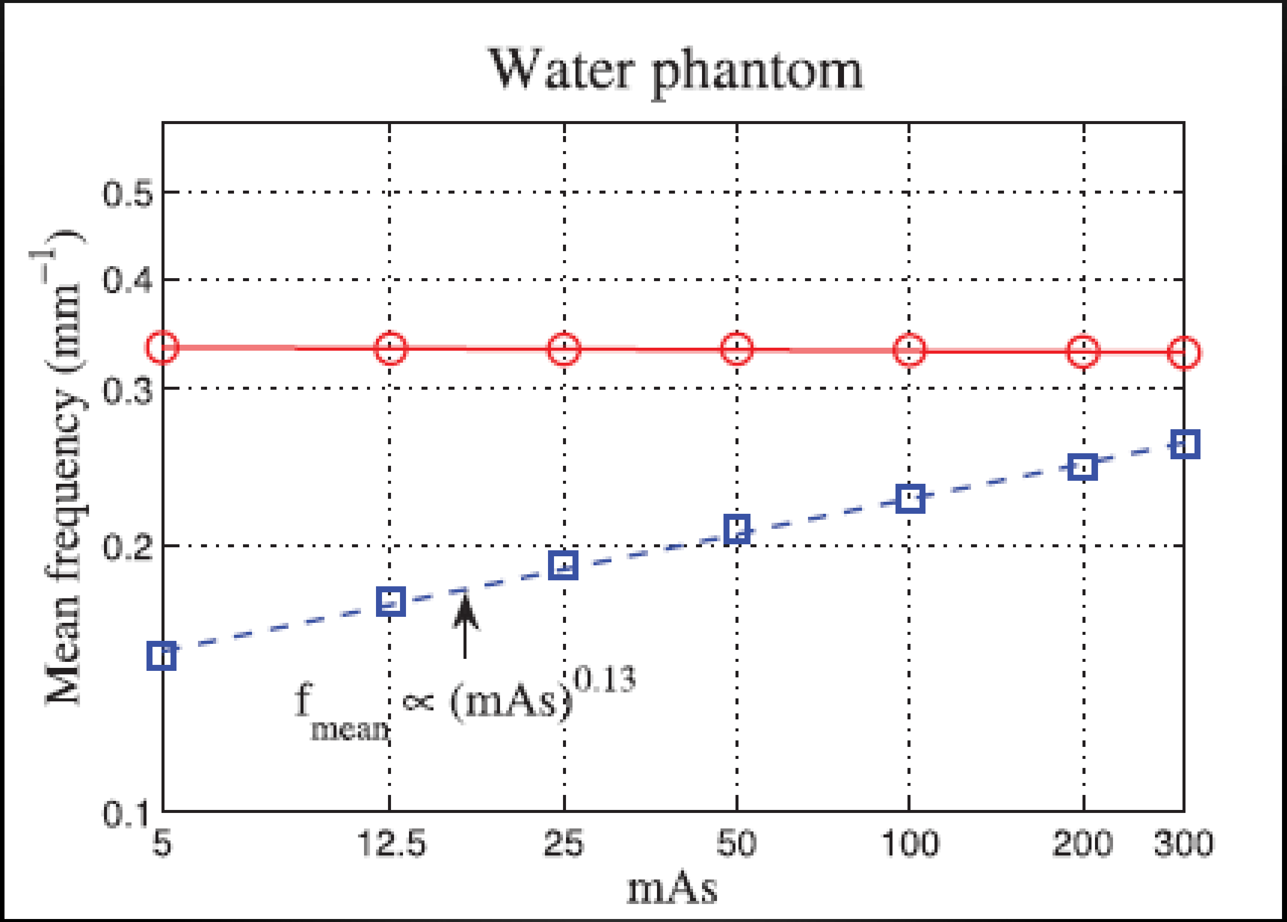
Li et al, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance" Medical Physics, Vol. 41, No. 4, April 2014

Peak Frequency for FBP and IR (Veo)



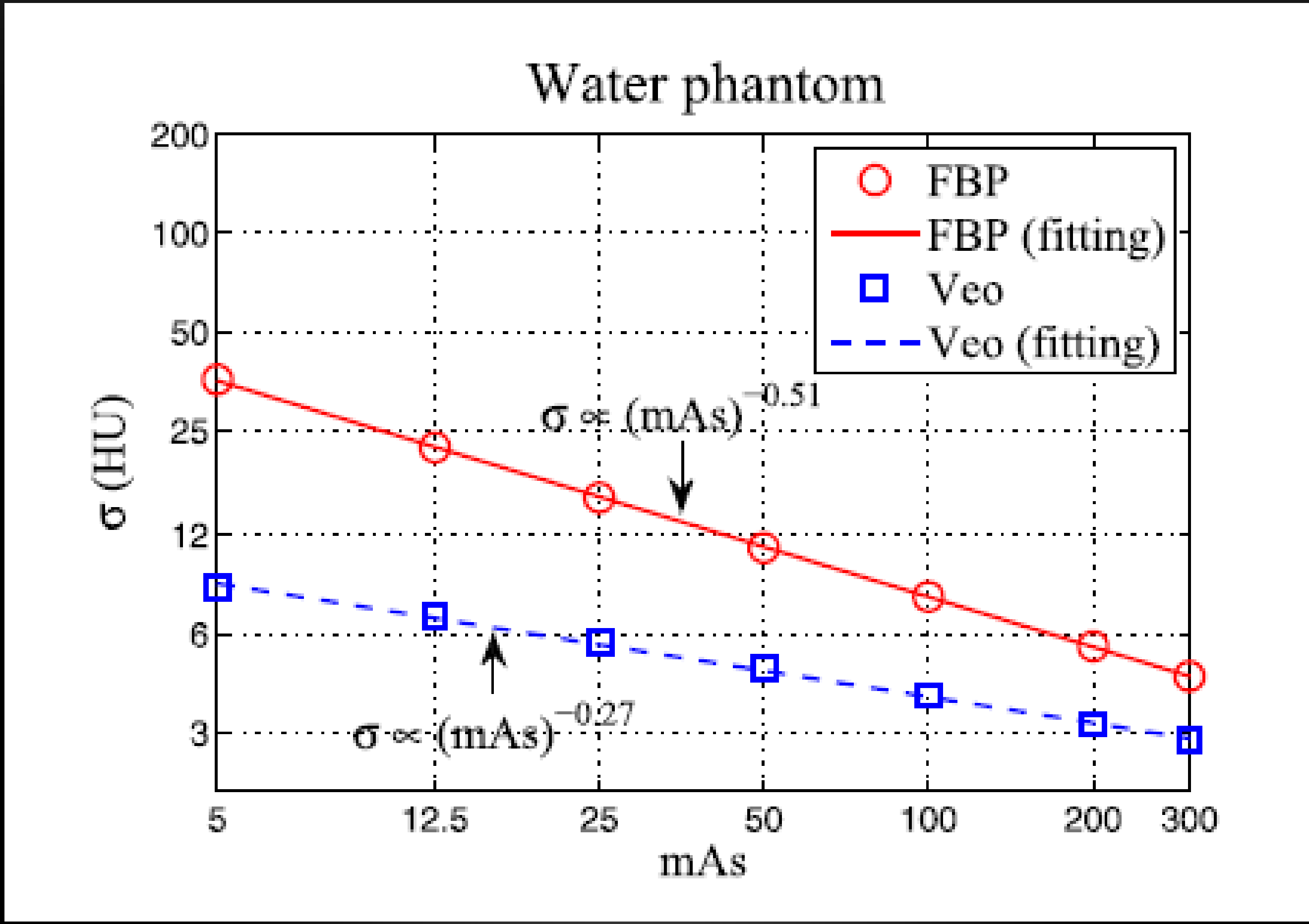
Li et al, “Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance” Medical Physics, Vol. 41, No. 4, April 2014

Mean Frequency for FBP and IR (Veo)



Li et al, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance" Medical Physics, Vol. 41, No. 4, April 2014

Noise vs. Dose for FBP and IR (Veo)



Li et al, "Statistical Model Based Iterative Reconstruction (MBIR) in clinical CT systems: Experimental assessment of noise performance" Medical Physics, Vol. 41, No. 4, April 2014

Implications for Protocol Optimization in IR

- For IR protocols, the conventional relationship between noise and dose ($\sigma = \alpha \cdot (mAs)^{-\beta}$, β= 0.5) may not be valid anymore. Re-assessment of this important relationship under different dose levels is needed.
- In Veo (GE), β is between 0.21 and 0.25, which means the noise standard deviation is much less sensitive to the dose change. A 50% dose reduction will result in only 15% to 19% increase in noise. In FBP, that amount of dose reduction will lead to 40% noise increase.

Implications for Protocol Optimization in IR

- Noise texture may impact the detectability of low contrast lesion, especially using high strength IR.
- In general, IR will not degrade the high contrast resolution due to the fact that most IR uses adaptive regularization.

Conclusion

- NPS is a comprehensive descriptor for CT image noise properties, specifically related to noise texture
- Nonlinear iterative reconstruction tends to shift peak frequency of NPS curve towards lower value, but it doesn't necessarily mean degradation of high contrast resolution
- Noise vs. dose relationship for FBP may not be valid for IR due to its nonlinear regularization used in the statistical model
- Optimization of CT IR-based protocols should consider the implication of its nonlinearity on NPS