Low Dose CT: Where do we stand now?

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U01 EB021183

GE imagination at work — Patent royalties received from GE Healthcare

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2

Outline

- Scientific foundation of radiation dose reduction;
- Low dose CT software method (1):
  Combination of denoising and the conventional filtered backprojection (FBP) reconstruction;
- Low dose CT software method (2):
  Combination of denoising and modeling of photon statistics in model based image reconstruction (MBIR);
- Challenges and opportunities in low dose CT software technologies
- Summary

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Scientific foundation of low dose CT

ALARA[1,2] principle: reduce radiation dose as low as it is reasonably achievable such that diagnostic performance is not compromised!

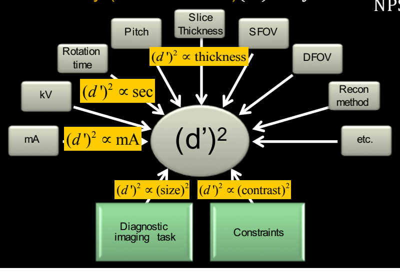
[1] ICRP, Publication 87 (2000)
[2] J. R. Haaga, *Am J Roentgenol*, (2001)

What is performance and how to quantify it?

- Signal quantification
  Signal amplitude: CT Number and integration over a finite size area
  Signal blurring: Point Spread Function (PSF) and modulation transfer function (MTF)
- Noise quantification
  Noise amplitude: Noise variance
  Noise power: Noise Power Spectrum (NPS)
- Overall performance quantification
  Contrast-to-noise ratio (CNR)
  Task-based detectability index $(d')^2$

Scientific foundation of low dose CT

Task-based detectability (ideal observer) $(d')^2 = \int d\mathbf{k} \frac{|T(\mathbf{k})MTF(\mathbf{k})|^2}{NPS(\mathbf{k})}$



Short-cut metric: CNR and Noise Variance?

Under the prewhitening condition, NPS is considered to be "white". This assumption helps reduce the detectability index to the more commonly used concept of CNR[1]:

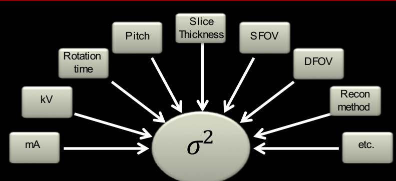
$$(d')^2 = \int d\mathbf{k} \frac{|T(\mathbf{k})MTF(\mathbf{k})|^2}{NPS(\mathbf{k})} = \frac{1}{\sigma^2}\int d\mathbf{k}\,|T(\mathbf{k})MTF(\mathbf{k})|^2 = \frac{S^2}{\sigma^2} = CNR^2$$

Since signal level does not change too much with scanning parameters except the tube potential, one can cheat a bit by studying noise variance and spatial resolution separately to assess "image quality/performance".

Cautions must be taken to avoid overly extrapolating conclusions.

[1] Burgess, JOSA (1999)

Scientific foundation of low dose CT

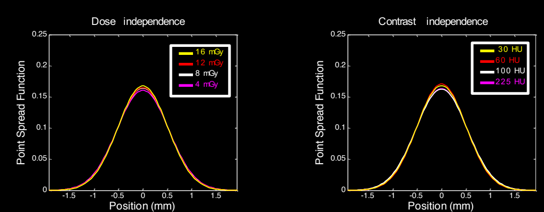


$$\propto f_{RECON} \times \frac{1}{DOSE} \times \frac{1}{e^{-\mu D}} \times \frac{1}{(\Delta x)^3 \Delta z}$$

Simplified cheat sheet to develop low dose CT techniques!

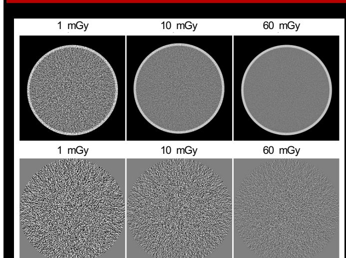
MTF Measurement: Dose/contrast dependence (FBP)

Spatial resolution is independent of dose and contrast.



Li, Garrett, Ge, Chen, *Med. Phys.* 41, 071911 (2014)

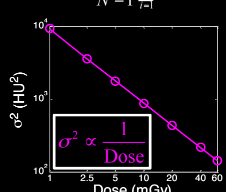
Noise Amplitude: Noise Variance (FBP)



K. Li, J. Tang, G.-H. Chen, *Med. Phys.* 41, 041906 (2014)

- Noise variance (σ^2) or noise standard deviation (σ)

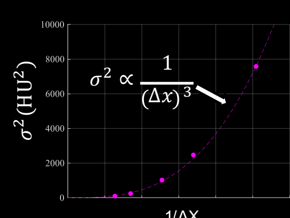
$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2$$

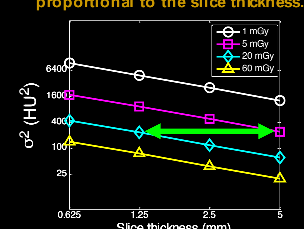


Noise amplitude: Slice thickness dependence (FBP)

Noise variance is inversely proportional to the cubic of Δx

Noise variance is inversely proportional to the slice thickness.

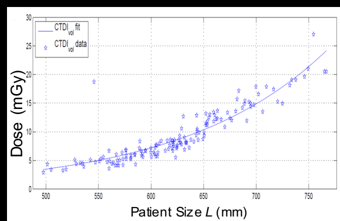




Noise amplitude: Patient size dependence (FBP)

$$\sigma^2 = \alpha \frac{\exp(uL)}{\text{Dose}}$$

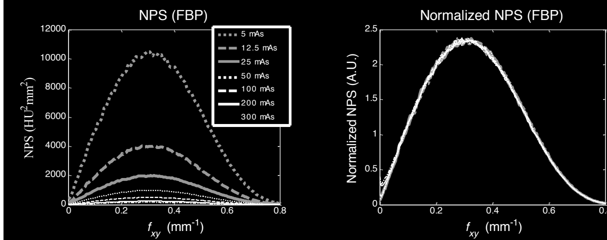
$$\text{Dose} = \frac{\alpha}{\sigma^2} \exp(uL)$$



Szczykutowicz, T. P., Bour, R. K., Pozniak, M., & Ranallo, F. N. Journal of Applied Clinical Medical Physics, 16, 2 (2015)

NPS: Scale invariance in NPS (FBP)

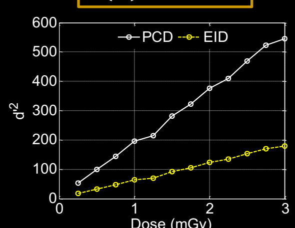
Dose scale invariance: The shape of the NPS is independent of radiation dose!



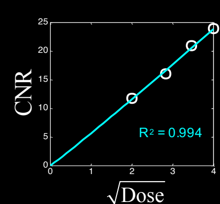
K. Li, J. Tang, G-H. Chen, *Med. Phys.* **41**, 041906 (2014)

Performance: Radiation Dose Dependence (FBP)

$(d')^2 \propto$ **Dose**



$\text{CNR} \propto \sqrt{\text{Dose}}$



Low dose CT software technologies demystified

Secret sauce in **NEW** low dose CT software technologies:

Develop software technologies to modify the functional dependence of either detectability or noise variance on the CT scanning parameters.

Objective of Low dose CT software technologies

Is low dose CT software technology all about noise reduction?

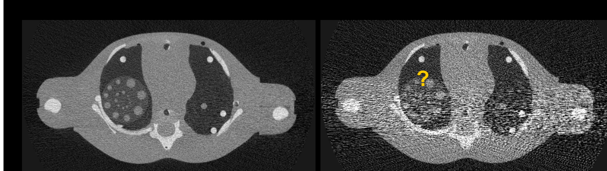
Well, noise reduction plus preserving image edges for the sake of spatial resolution.

But is that all?

Low dose CT: Reduction of Noise and Noise streaks!

Reference dose

25% of Reference dose



Gomez-Cardona et al, SPIE (2017)

18

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Low dose CT techniques: Hardware

- CT system hardware improvements
  - Quantum and geometrical detector efficiency[1,2]
  - Modification of pre- and post-patient collimators[3]
  - Development of patient-oriented beam shaping filters (e.g. bowtie filters)[4]
  - Incorporation of angular and longitudinal tube current modulation[5]
  - Optimization of tube potential control[6]

Software advances need to be in synergy with hardware advances to achieve improved imaging performance at low dose levels

[1] W. C. Barber, et. al., *Proc SPIE* (2009)
[2] L. M. Hamberg, et. al., *Radiology*, (2003)
[3] G. Vogtmeier, et. al., *Proc SPIE* (2008)
[4] N. Mail, et. al., *Med Phys* (2009)
[5] M. K. Kalra, et. al., *Radiology* (2004)
[6] L. Yu, et. al., *Radiographics* (2011)
[7] Y. J. Suh, et. al., *Radiology* (2013)

20

Low dose CT techniques: Software

- There is a wide spectrum of software approaches that aim to enable low dose CT, some of them are:
  - Analytical reconstruction methods + denoising
    - FBP + Image domain post-processing
    - Log-transform domain denoising + FBP
    - Raw data domain denoising + FBP
  - Model based Iterative reconstruction (MBIR) methods
    - Statistical model
    - Noise suppression regularizer model (denoising process)

21

Low dose CT techniques: Software
FBP reconstruction + Image domain post-processing

25% of Reference dose

Image domain denoising?

1 iterations

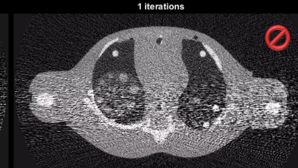


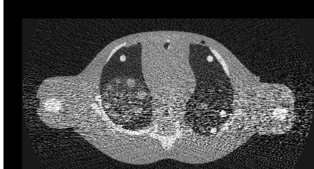
Image domain denoising can be challenging when severe noise streaks are present and anatomical structures are already highly distorted[1]

[1] H. Zhang, et.al., Med Phys (2017)

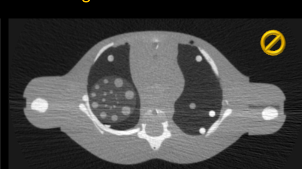
22

Low dose CT techniques: Software
Log-transformed data denoising + FBP reconstruction

25% of Reference dose



Log-transformed domain



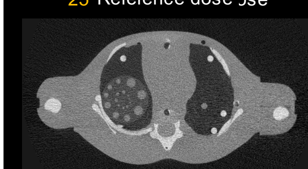
Despite the success of some techniques,[1,2]
it is still challenging to mitigate noise streaks due to amplified variability after performing log-transform

[1] T. Li, et. al., *IEEE Trans Nucl Sci* (2004)
[2] J. Wang, et. al., *IEEE Trans Med* (2006)

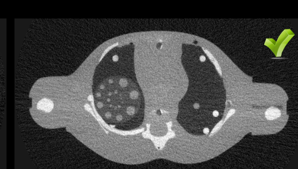
23

Low dose CT techniques: Software
Raw measured data denoising + FBP reconstruction

25' Reference dose ɔse



Raw domain?



Working directly with the measured raw data facilitates correction of photon-starved measurements

24

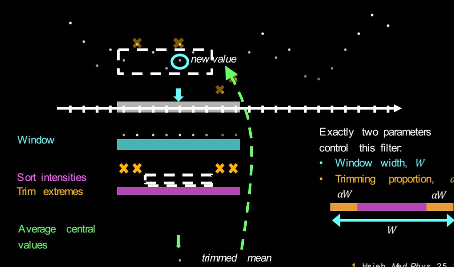
Low dose CT techniques: Software
Raw measured data denoising + FBP reconstruction

- Some examples of methods reported in the literature
  - Adaptive trimmed mean filter[1]
  - Multi-dimensional adaptive filtering[2]
  - Spline-based penalized-likelihood sinogram[3]
  - Adaptive noise model-based bilateral filtering for streaking and noise reduction in multi-slice CT[4]
  - Multi-dimensional tensor-based adaptive filter[5]
  - Anisotropic diffusion has been shown to reduce noise while accurately localizing and preserving edge structural information[6]

[1] J. Hsieh, *Med Phys*, 25, 11 (1998)
[2] M. Kachelrieß, O. Watzke, W. Kalender, *Med Phys*, 28, 4,(2001)
[3] P. J. L. Rivière, D. M. Billmire, *IEEE Trans Med Imag*, 24, 1 (2005)
[4] L. Yu, et. al., *Proc. SPIE*, 7622, (2010)
[5] M. Knaup, et. al., *Proc. SPIE*, 9412 (2015)
[6] O. Demirkaya, *Proc SPIE* (2001)

25

Two categories of filters: Trimmed mean filter



Exactly two parameters control this filter:
- Window width, W
- Trimming proportion, α

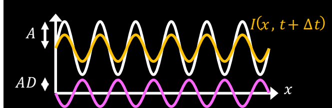
αW αW

W

1. Hsieh, *Med Phys*, 25, 11 (1998)
2. Bednar and Watt, (1984)
3. Dabov et al, BM3D, IEEE (2007)

Two types of filters: spatial filter (diffusion example)

$I(x,t) = 1 + A\sin(x-t)$



1D Diffusion Equation $\frac{\partial I}{\partial t} = D\frac{\partial^2 I}{\partial x^2}$

$$\frac{\partial I}{\partial t} \approx \frac{I(x,t+\Delta t) - I(x,t)}{\Delta t}$$

$$D\frac{\partial^2 I}{\partial x^2} = -AD\sin(x-t)$$

$$I(x,t+\Delta t) \approx I(x,t) - \Delta t \cdot AD\sin(x-t)$$

Two features make diffusion as a denoising process possible
- The polarity of the 2nd order partial derivative is opposite that of the noise
- The modulation of this term is non-expansive

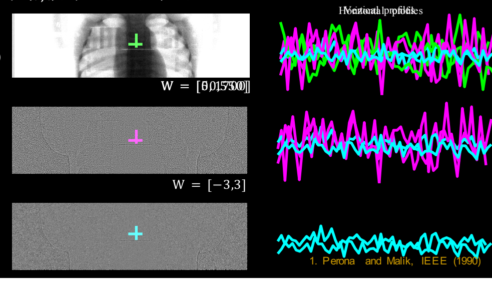
Diffusion: A denosing process

$$\frac{\partial I}{\partial t} = \nabla \cdot (D(x,t)\nabla I) = \nabla D \cdot \nabla I + D\nabla^2 I \qquad I(x,t+\Delta t) \approx I(x,t) + \nabla D \cdot \nabla I + D\nabla^2 I$$

Noisy raw counts $I(u,v,t=0)$

$\nabla D \cdot \nabla I$

$D\nabla^2 I$



1. Perona and Malik, IEEE (1990)

Remarks on diffusion denoising filter

- The dot product term generates the desired polarity for noise cancellation already, there is no need for the Laplacian term for denoising purpose! That is perhaps one of the reasons that this term was dropped in the numerical implementation in the original paper by Perona and Malik.[1]
- Numerically, the computation of higher order derivatives involves the average over more neighboring pixels and thus smooth image edges more than the computation of only first order derivatives.
- More often used bi-lateral filters can be considered as a special case of the diffusion filter when the diffusion coefficient function, D(x,t), is selected to be a Gaussian-like function.[2]

1. Perona and Malik, IEEE (1990)
2. Barash, IEEE (2002)

29

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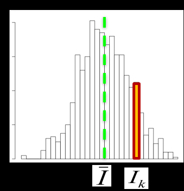
Low dose CT techniques: MBIR

Given a single sample of stochastic measurement of x-ray photons, the best we know is the probability of the occurrence, that is given by the Poisson statistics model

$$P(I_k) = e^{-\bar{I}} \frac{\bar{I}^{I_k}}{I_k!}$$

Joint probability of a data set:

$$P(\{I_k\} \mid \mu) = \prod_{k=1}^{M} e^{-\bar{I}_k} \frac{\bar{I}_k^{\,I_k}}{I_k!}$$



31

Low dose CT techniques: MBIR

What is the probability of estimating the attenuation distribution of an image object given the measured data set in your hand?

Bayesian rule $P(\{N_i\} \mid \mu) \Rightarrow P(\mu \mid \{N_i\}) = \frac{P(\{N_i\} \mid \mu) P(\mu)}{P(\{N_i\})}$

Image Reconstruction problem statement:

Seek for an estimation to maximize the probability!

32

Low dose CT techniques: MBIR

- Maximizing the Log-likelihood function:

$$\tilde{\mu} =: \arg\max_{\mu} [\ln P(\mu(\vec{x}, E) \mid \{N_i\})]$$
$$= \arg\max_{\mu} [\sum_{i=1}^{M} (-\bar{N}_i + N_i \ln \bar{N}_i - \ln N_i) + \ln P(\mu)]$$

- Under the following quadratic approximation:

$$\tilde{\mu} := \arg\min_{\mu} [\frac{1}{2} (\vec{y} - A\vec{\mu})^T D (\vec{y} - A\vec{\mu}) + \lambda R(\vec{\mu})]$$

$$D = diag\{N_1, N_2, \cdots, N_M\}$$

33

Low dose CT techniques: MBIR

$$\tilde{\mu} := \arg\min_{\mu} [\frac{1}{2} (\vec{y} - A\vec{\mu})^T D (\vec{y} - A\vec{\mu}) + \lambda R(\vec{\mu})]$$

Data consistency driven image update:

$$\vec{v}_{k+1} = \vec{\mu}_k + PA^T D(\vec{y} - A\vec{\mu}_k)$$

Denoising:

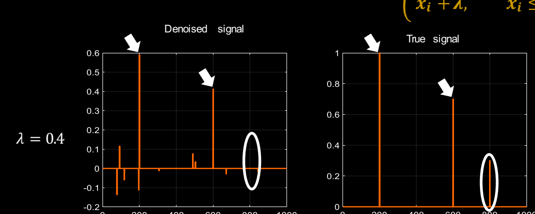
$$\vec{\mu}_{k+1} =: \arg\min_{\mu} \left\{ \frac{1}{2} \| \vec{\mu} - \vec{v}_{k+1} \|_{P^{-1}}^2 + \lambda R(\vec{\mu}) \right\}$$

1. Combettes and Wijs, Multiscale Model. Simul., Vol. 4: 1168(2005)
2. Li Y, Niu K, Tang J, Chen G-H. Proc. SPIE, 2014. p. 90330U-U-8.

34

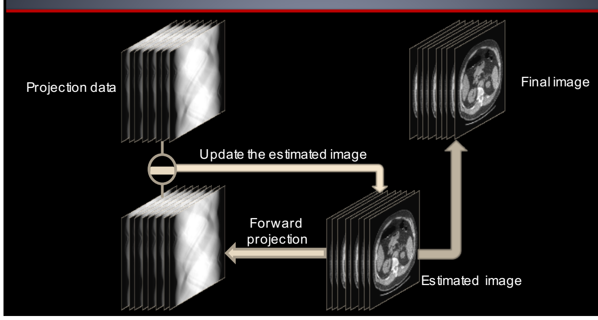
Low dose CT techniques: MBIR

$$S(x_i) = \text{argmin}_x \left[\frac{1}{2} (x - x_i)^2 + \lambda |x| \right], \quad S(x_i) = \begin{cases} x_i - \lambda, & x_i \ge \lambda \\ 0, & -\lambda < x_i < \lambda \\ x_i + \lambda, & x_i \le -\lambda \end{cases}$$



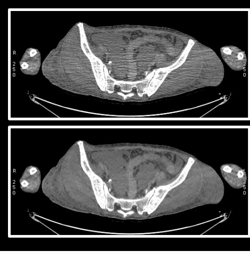
35

Model-Based Iterative Reconstruction (MBIR)



Benefits of MBIR

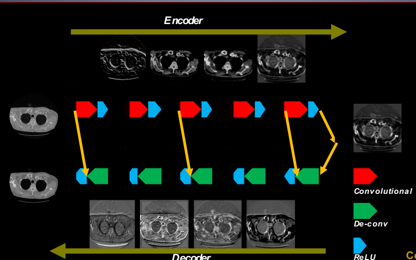
Reduce streaks caused by low photon count (high noise) projection data and reduced noise level



Benefit of MBIR: Clinical Case

This Abdomen/Pevis CT scan covers ~40 cm in the z direction with a 0.7 mSv effective dose. The BMI of this patient is 19.4.

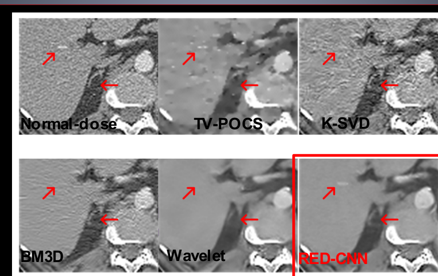
Future software technique: Deep learning?



Courtesy of Dr. GE Wang

Biomed Opt Express 2017 Feb 1; 8(2): 679–694

Future software technique: Deep learning?



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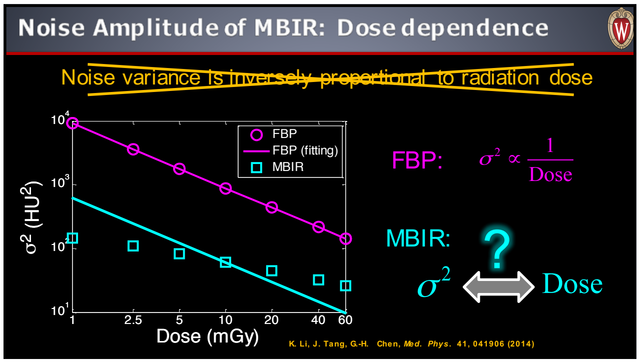
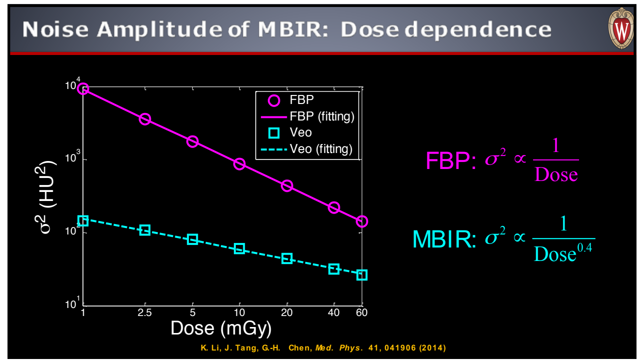
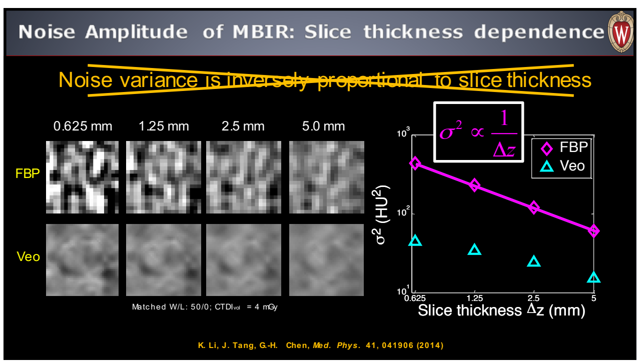
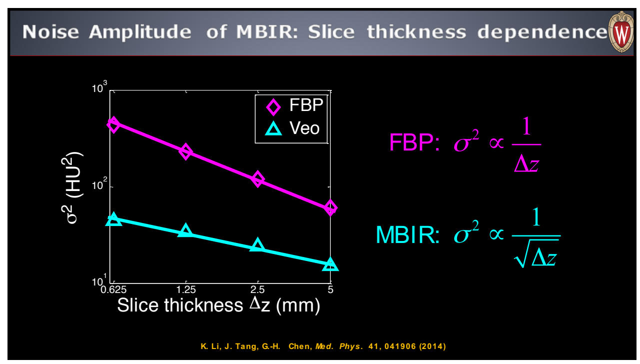
From Linear FBP to Nonlinear MBIR Reconstruction

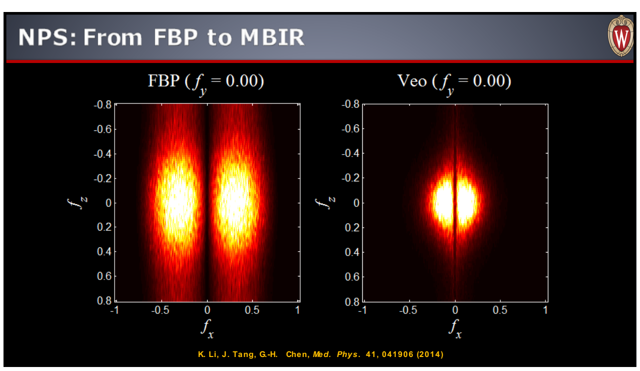
Question: How would our cheat sheet change when a nonlinear model based iterative reconstruction or other nonlinear denoising technique is used?

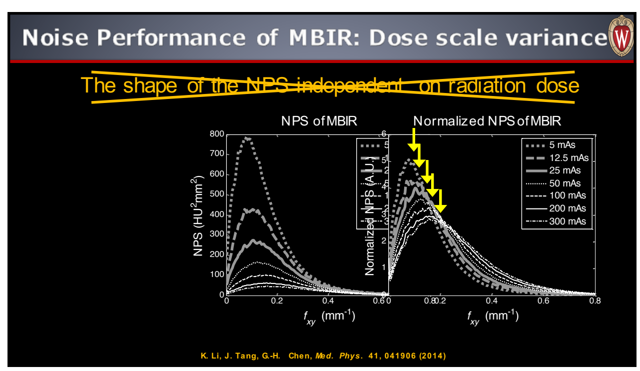

Noise Amplitude of MBIR: Dose dependence
Noise variance is inversely proportional to radiation dose
FBP
FBP (fitting)
MBIR
σ2 (HU2)
Dose (mGy)
FBP: $\sigma^2 \propto \frac{1}{\text{Dose}}$
MBIR:
?
σ^2 Dose
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)


Noise Amplitude of MBIR: Dose dependence
FBP
FBP (fitting)
Veo
Veo (fitting)
σ2 (HU2)
Dose (mGy)
FBP: $\sigma^2 \propto \frac{1}{\text{Dose}}$
MBIR: $\sigma^2 \propto \frac{1}{\text{Dose}^{0.4}}$
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)

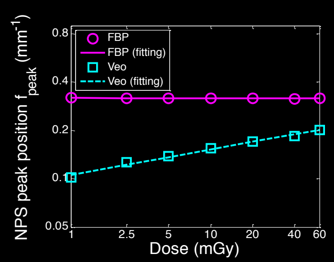

Noise Amplitude of MBIR: Slice thickness dependence
Noise variance is inversely proportional to slice thickness
0.625 mm
1.25 mm
2.5 mm
5.0 mm
FBP
Veo
$\sigma^2 \propto \frac{1}{\Delta z}$
σ2 (HU2)
Slice thickness Δz (mm)
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)


Noise Amplitude of MBIR: Slice thickness dependence
FBP
Veo
σ2 (HU2)
Slice thickness Δz (mm)
FBP: $\sigma^2 \propto \frac{1}{\Delta z}$
MBIR: $\sigma^2 \propto \frac{1}{\sqrt{\Delta z}}$
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)


NPS: From FBP to MBIR
FBP (f_y = 0.00)
Veo (f_y = 0.00)
f_z
f_x
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)


Noise Performance of MBIR: Dose scale variance
The shape of the NPS independent on radiation dose
NPS of MBIR
Normalized NPS of MBIR
5 mAs
12.5 mAs
25 mAs
50 mAs
100 mAs
200 mAs
300 mAs
f_{xy} (mm^{-1})
K. Li, J. Tang, G.-H. Chen, Med. Phys. 41, 041906 (2014)

Noise Performance of MBIR: Dose scale variant

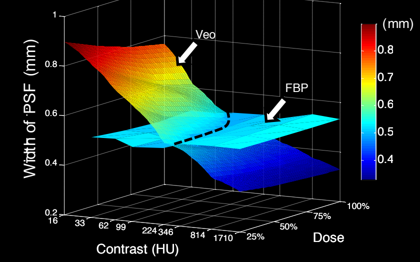


FBP: f_{peak} = const.

MBIR: $f_{peak} \propto (\text{dose})^{\frac{1}{5}}$

K. Li, J. Tang, G-H. Chen, *Med. Phys.* 41, 041906 (2014)

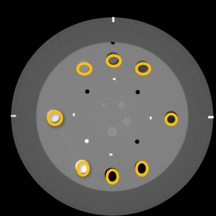
Spatial Resolution: Joint Dependence on Image Contrast and Radiation Dose



Li, Garrett, Ge, Chen, *Med. Phys.* 41, 071911 (2014)

Another challenge in low dose CT: CT number bias

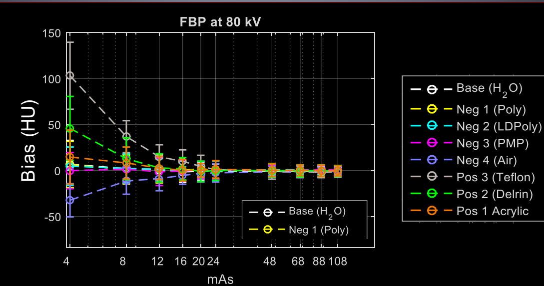
- Catphan® 600 phantom
- Acquisition parameters:
  - 50 repeated scans
  - Axial acquisition
  - Detector coverage: 20 mm x 0.625 mm
  - Head bowtie
  - Three kV levels: 80, 100, 120
  - 10 reduced mAs levels:, 4-104
  - Ground truth mAs: 1400
- Reconstruction parameters
  - FBP and MBIR reconstruction methods
  - Slice thickness 0.625 mm
  - DFOV: 22 cm



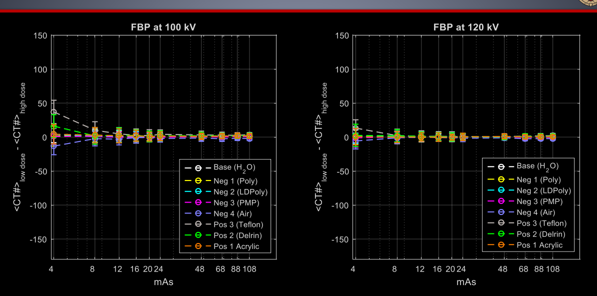
- Air
- PMP
- LDPE
- Water
- Polystyrene
- Acrylic
- Delrin ®
- Teflon ®

51

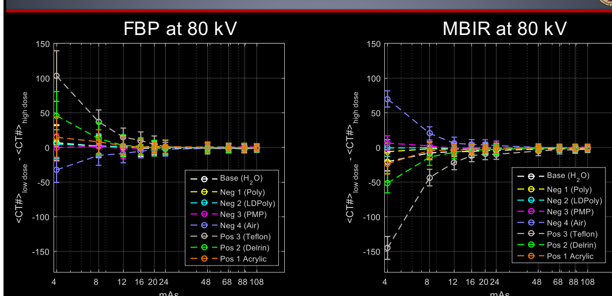
CT number bias $= \langle CT\#(D) \rangle - \langle CT\#(D_{High}) \rangle$



CT number bias: Different tube potentials



CT number bias: MBIR vs. FBP



Outline

- Scientific foundation of radiation dose reduction;
- Low dose CT software method (1):
  Combination of denoising and the conventional filtered backprojection (FBP) reconstruction;
- Low dose CT software method (2):
  Combination of denoising and photon statistics modeling in model based image reconstruction (MBIR);
- Challenges and opportunities in low dose CT software technologies
- Summary

Low dose CT Software Technologies: Summary

- Low dose CT can be achieved by combining denoising techniques in the raw detector counts domain to reduce noise while suppressing photon starvation noise streaks;
- Low dose CT can also be iteratively achieved by incorporating noise streak suppression in the reconstruction process followed by a denoising filtration process;
- The conventional functional dependence of imaging performance on scanning parameters demonstrates non-linear behavior in image quality assessment;
- Low dose CT also increases CT number bias.

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57