Overview of CT reconstruction and denoising strategies

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Acknowledgements

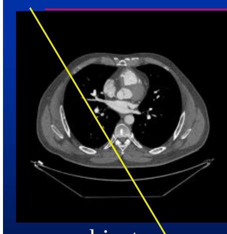
Jean-Baptiste Thibault, Bruno DeMan, Jiang Hsieh (GE Healthcare)
Karl Stierstorfer, Thomas Flohr (Siemens Healthcare)
Sandra Halliburton (Philips Healthcare)
Erin Angel (Toshiba America Medical Systems)
Guang-Hong Chen (U. Wisconsin)
Jeffrey Fessler (U. Michigan)
Scott Hsieh, Dominik Fleischmann (Stanford)

COI Disclosure:
Research support from GE Healthcare and Philips Healthcare

Outline

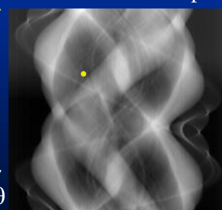
- Introduction
- Model based reconstruction
- Statistical reconstruction
- Non-linear/non-stationary effects
- Conclusions

Forward problem



forward projector

r



θ

object

expected data

Inverse problem

reconstruction algorithm

From the measured projection data, what is the object that produced it?

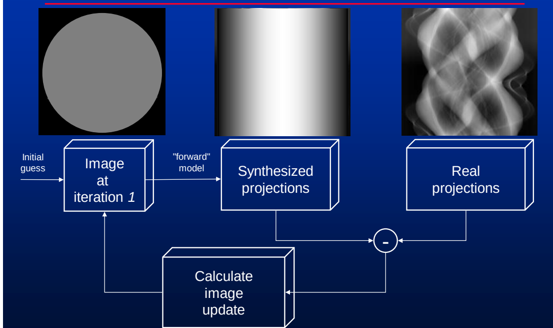
Analytical reconstruction

- Image is produced directly from the measured data
- E.g., filtered backprojection (FBP)

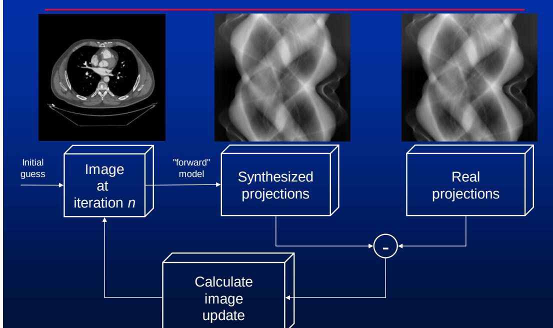
$$f(x,y) = \int_0^{\pi} \int_{-\infty}^{\infty} P(k,\theta)\, |k|\, e^{i2\pi kr}\, dk\, d\theta \quad \text{with } r = x\cos\theta + y\sin\theta$$

- Very efficient
- If the data is perfect the image is exact

Iterative reconstruction

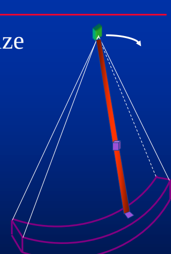


Iterative reconstruction



Build in an accurate physics model

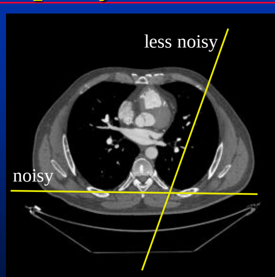
- Real focal spot and detector size
- Finite size voxel
- True ray path (divergent rays)
- Beam hardening
- Known system imperfections
- Motion
- Reconstruction algorithm attempts to correct for effects built into the model



Taking uncertainty into account

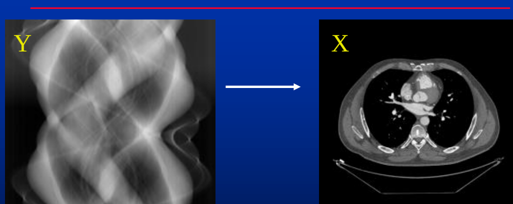
If Warren Buffet and I give you stock predictions, do you trust them equally?

Are all measured rays equally reliable?



Analytical recon treats all rays as equally accurate

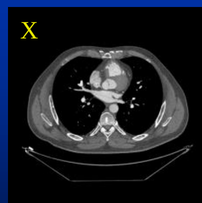
Optimization method



X = object "most likely" to produce data Y

can include measurement uncertainty (noise, etc.) and physical imperfections

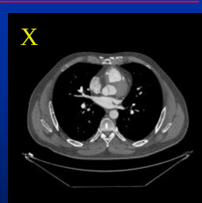
Optimization method



X = object "most likely" to produce data Y

Problems: lack of convergence, noise amplification

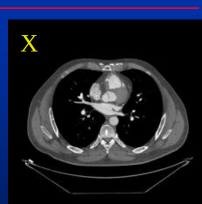
Regularization



X = (object "most likely" to produce data Y) given (constraints, prior "knowledge")

measurement uncertainty — promote smoothness

Regularization

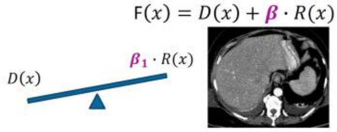


minimize (data disagreement) + β (difference of nearby pixels)

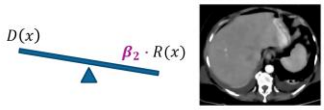
measurement uncertainty — key parameter, smoothes image

Noise Constraint

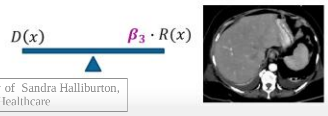
$$F(x) = D(x) + \beta \cdot R(x)$$



= too noisy



= too smooth



= “just right”

courtesy of Sandra Halliburton, Philips Healthcare

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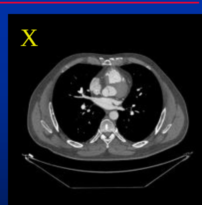
Regularization



minimize (data disagreement) + β (difference of nearby pixels except at edges)

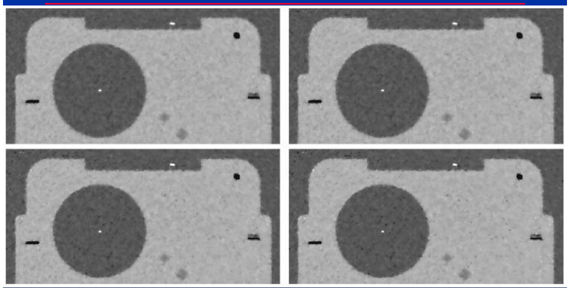
more parameters

Edge-preserving smoothing

Compare local signal differences to expected noise

- low: suppress them (smoothing)
- large: retain them (edge-preserving)
- medium: smooth a little

image appearance



edge preserving noise suppression “prior” favors "plateaus" with sharp edges

Thibault, et al, Med Phys 34, 4526-44 , 2007.

Advantages of Non-Linear Regularization versus Linear Filtering

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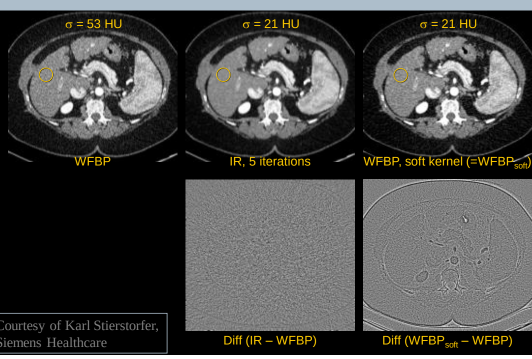
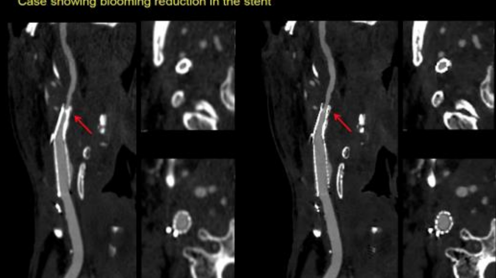


Courtesy of Karl Stierstorfer, Siemens Healthcare

Clinical Example

Case showing blooming reduction in the stent



imagination at work

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Courtesy of Jiang Hsieh, GE Healthcare

Regularization

- Examples
  - Quadratic
  - Huber
  - Total variation
  - Wavelets
  - Dictionary learning
- Regularizer can introduce
  - Nonlinearity
  - Non-stationarity
  - Bias

Image quality assessment for linear CT systems

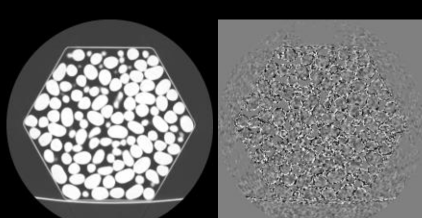
(Quasi) Noise Linearity

FBP reconstruction Corresponding noise-only image

Slide courtesy of Guang-Hong Chen, University of Wisconsin

Image quality assessment for nonlinear CT systems

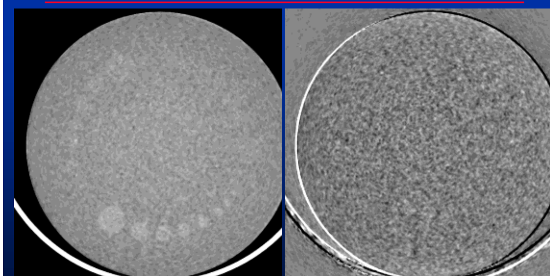
Noise Nonlinearity



MBIR reconstruction Corresponding noise-only image

Slide courtesy of Guang-Hong Chen, University of Wisconsin

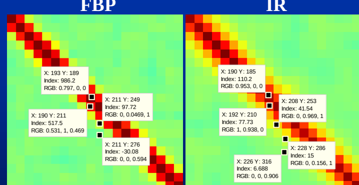
Low contrast phantom



difference of Veo recons of two slices

Regularizers operate in 3D

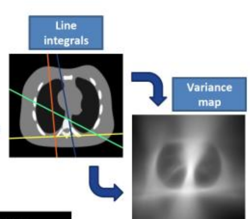
FBP IR

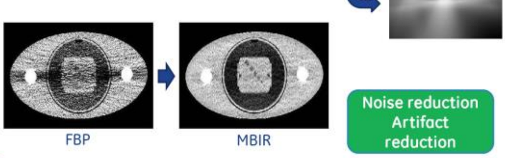


- Slice direction covariance measured in a uniform image region
- IR has lower but wider covariance
- Slices are effectively thicker in low contrast region

Noise Model

- Based on x-ray physics (Poisson-Gaussian counting process)
- Relative degree of confidence in each measurement as it relates to the image
- Advanced modeling for low signal and electronic noise

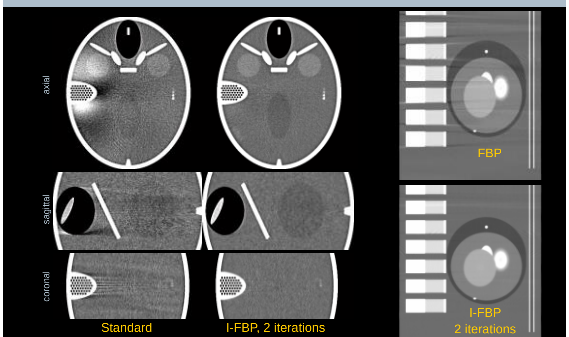




GE imagination at work

Courtesy of Jiang Hsieh, GE Healthcare

Cone-beam Artifact Reduction by IR



courtesy of Karl Stierstorfer, Siemens Healthcare

Cardiac CT

IR w/ motion artifact correction

Yuki et al., JCCT, 2014

courtesy of Sandra Halliburton, Philips Healthcare

Iterative reconstruction modeling all the physics

- very powerful
- iterates in both raw data and image domains
- can include: statistical uncertainty, system physics, "prior knowledge", edge-preserving noise reduction
- yields: improved low contrast resolution, artifact reduction
- computationally expensive

General Approach

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For the different objectives of iterative reconstruction, choose the domain most efficient to accomplish them:

Need low signal data enhancement?
→ work in the raw data domain; apply statistical modeling

Need (cone beam) artifact reduction?
→ need a full raw data/image loop including a forward projection of images

Need noise reduction?
→ best apply iterative regularization in image domain

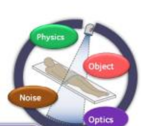
courtesy of Karl Stierstorfer, Siemens Healthcare

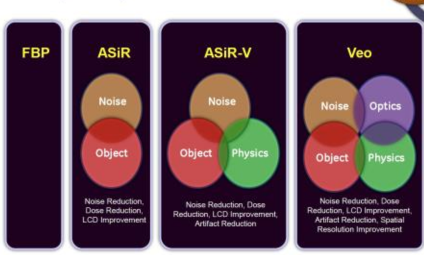
CT image reconstruction

- FBP
- iterative reconstruction that model statistics and x-ray physics
  - multiple iterations between raw data and image domains
- "Statistical" reconstruction
  - edge-preserving noise reduction in image and/or raw data domains
  - much faster than full iterative recon

Reconstruction Algorithms

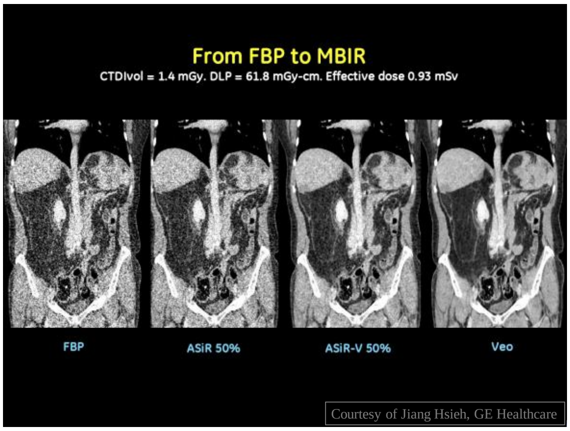
- Primary goal: dose reduction
- Speed vs. performance tradeoff

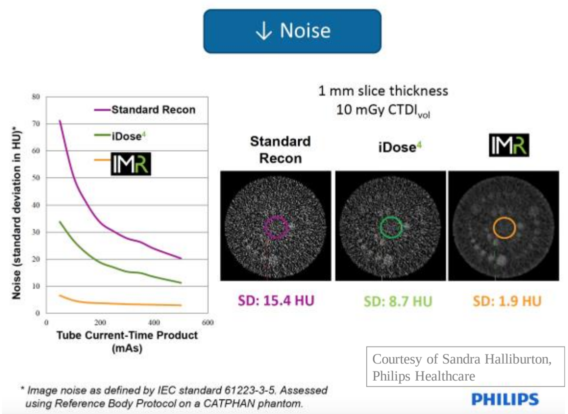




GE imagination at work

Courtesy of Jiang Hsieh, GE Healthcare


From FBP to MBIR
CTDIvol = 1.4 mGy, DLP = 61.8 mGy-cm, Effective dose 0.93 mSv
FBP
ASiR 50%
ASiR-V 50%
Veo
Courtesy of Jiang Hsieh, GE Healthcare


↓ Noise
Standard Recon
iDose4
IMR
Noise (standard deviation in HU)*
Tube Current-Time Product (mAs)
1 mm slice thickness
10 mGy CTDIvol
Standard Recon
iDose4
IMR
SD: 15.4 HU
SD: 8.7 HU
SD: 1.9 HU
Courtesy of Sandra Halliburton, Philips Healthcare
* Image noise as defined by IEC standard 61223-3-5. Assessed using Reference Body Protocol on a CATPHAN phantom.
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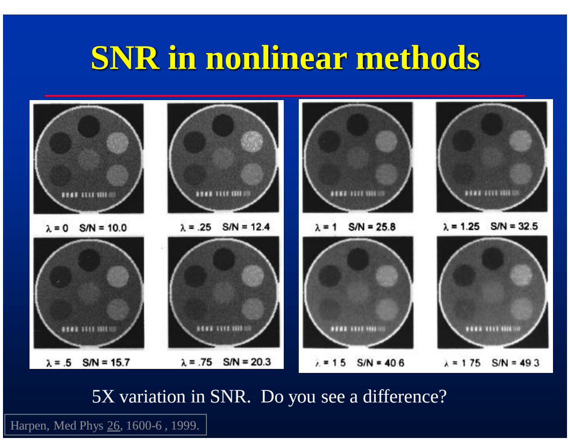
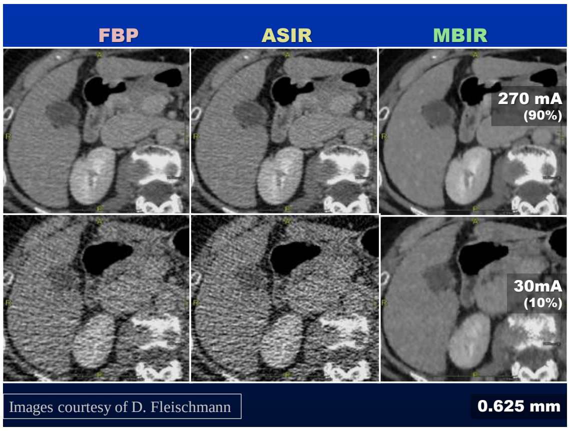
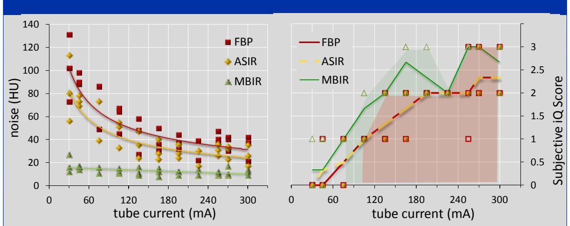

SNR in nonlinear methods
λ = 0 S/N = 10.0
λ = .25 S/N = 12.4
λ = 1 S/N = 25.8
λ = 1.25 S/N = 32.5
λ = .5 S/N = 15.7
λ = .75 S/N = 20.3
λ = 1.5 S/N = 40.6
λ = 1.75 S/N = 49.3
5X variation in SNR. Do you see a difference?
Harpen, Med Phys 26, 1600-6 , 1999.

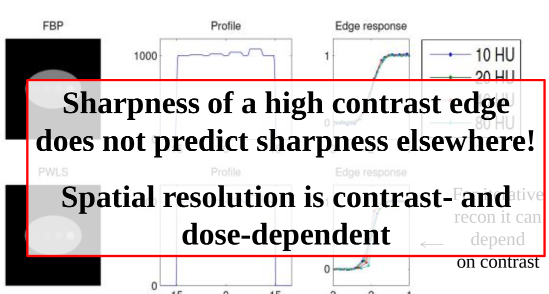


Effect of Dose on Noise and Image Quality



Standard deviation in a uniform region does not predict image quality!

Spatial resolution in IR depends on contrast



Adapted from slide courtesy of Jeff Fessler

Vendor product names

	edge-preserving noise reduction (in one domain)	iterative recon including model of data statistics	iterative recon modeling statistics and physics
GE	ASIR	ASIR-V	Veo
Philips	iDose[4]	IMR	
Siemens	IRIS, SAFIRE	ADMIRE	
Toshiba	QDS/ BOOST	AIDR 3D	FIRST

CT image reconstruction

- FBP (linear)
  Linear. Resolution is independent of contrast.
  Noise predicts IQ.
- "Statistical" reconstruction (non-linear)
  edge-preserving noise reduction
- Model-based iterative reconstruction (non-linear)
  most effective noise and artifact reduction
  slow
- Hybrid methods
- Non-linear methods have contrast-dependent noise and resolution behavior

Thank you!

Conclusions

- Analytical reconstruction (e.g., FBP) is fast and ideal when raw data is "perfect"
- Tremendous advance in statistical and iterative reconstruction, certain to continue to evolve
- Impact is highest when data quality is poor
  - low dose, large patients
- Significant dose reductions
- Differences among methods
- We need new image quality metrics