

Model-based image reconstruction for low-dose X-ray CT

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Former MS / undergraduate students

- Kevin Brown, Philips
- Meng Wu, Stanford
- ...

Statistical image reconstruction: a CT revolution

- A picture is worth 1000 words
- (and perhaps several 1000 seconds of computation?)



Thin-slice FBP

Seconds



ASIR

A bit longer



Statistical

Much longer

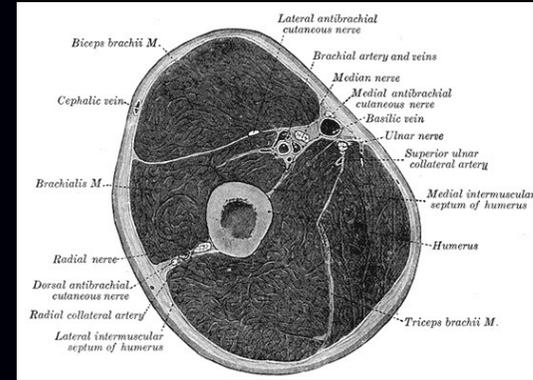
(Same sinogram, so all at same **dose**)

Why statistical/iterative methods for CT?

- Accurate **physics** models
 - X-ray spectrum, beam-hardening, scatter, ...
⇒ reduced artifacts? quantitative CT?
 - X-ray detector spatial response, focal spot size, ...
⇒ improved spatial resolution?
 - detector spectral response (*e.g.*, photon-counting detectors)
⇒ improved contrast?
- Nonstandard **geometries**
 - transaxial truncation (wide patients)
 - long-object problem in helical CT
 - irregular sampling in “next-generation” geometries
 - coarse angular sampling in image-guidance applications
 - limited angular range (tomosynthesis)
 - “missing” data, *e.g.*, bad pixels in flat-panel systems
- Appropriate models of (data dependent) measurement **statistics**
 - weighting reduces influence of photon-starved rays (*cf.* FBP)
⇒ reducing image noise or X-ray **dose**

and more...

- **Object** constraints / priors
 - nonnegativity
 - object support
 - piecewise smoothness
 - object sparsity (e.g., angiography)
 - sparsity in some basis
 - motion models
 - dynamic models
 - ...



Henry Gray, Anatomy of the Human Body, 1918, Fig. 413.

These constraints may help reduce image artifacts or noise or **dose**.

Disadvantages?

- Computation **time** (super computer)
- Must reconstruct entire FOV
- Complexity of models and software
- Algorithm **nonlinearities**
 - Difficult to analyze resolution/noise properties (cf. FBP)
 - Tuning parameters
 - Challenging to characterize performance / assess image quality

“Iterative” vs “Statistical”

- Traditional *successive substitutions* iterations
 - e.g., Joseph and Spital (JCAT, 1978) bone correction
 - usually only one or two “iterations”
 - not statistical
- **Algebraic** reconstruction methods
 - Given sinogram data \mathbf{y} and system model \mathbf{A} , reconstruct object \mathbf{x} by “solving” $\mathbf{y} = \mathbf{A}\mathbf{x}$
 - ART, SIRT, SART, ...
 - iterative, but typically not statistical \implies limited (if any) dose reduction
 - Iterative filtered back-projection (FBP):

$$\mathbf{x}^{(n+1)} = \mathbf{x}^{(n)} + \underbrace{\alpha}_{\text{step size}} \text{FBP} \left(\underbrace{\mathbf{y}}_{\text{data}} - \underbrace{\mathbf{A}\mathbf{x}^{(n)}}_{\text{forward project}} \right)$$

- **Statistical** reconstruction methods now come in several flavors:
 - Image domain
 - Sinogram domain
 - Fully statistical (both)
 - Hybrid methods (e.g., AIR, SPIE 7961-18, 2011, Bruder *et al.*)

Examine these in more detail next to consider **dose**.

“Statistical” methods: Image domain

- Denoising methods



- Relatively **fast**, even if iterative
- Remarkable advances in denoising methods in last decade



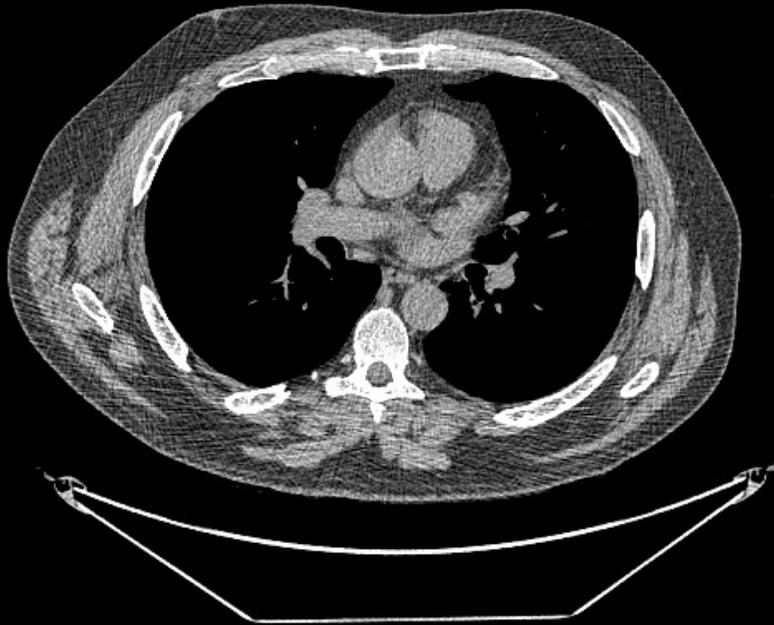
Zhu & Milanfar, T-IP, Dec. 2010, using “steering kernel regression” (SKR) method

Challenges:

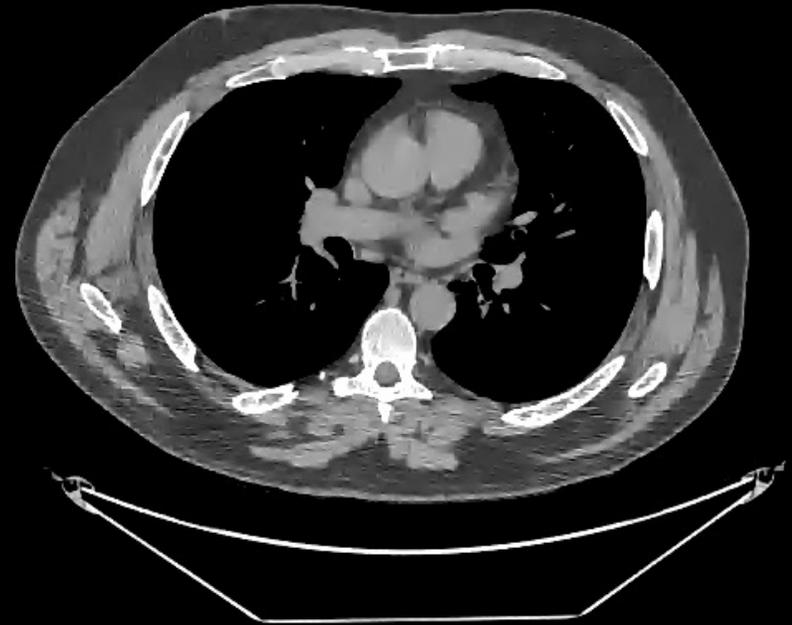
- Typically assume *white noise*
- Streaks in low-dose FBP appear like edges (highly correlated noise)

Example (denoising by wavelet soft thresholding with spin cycling)

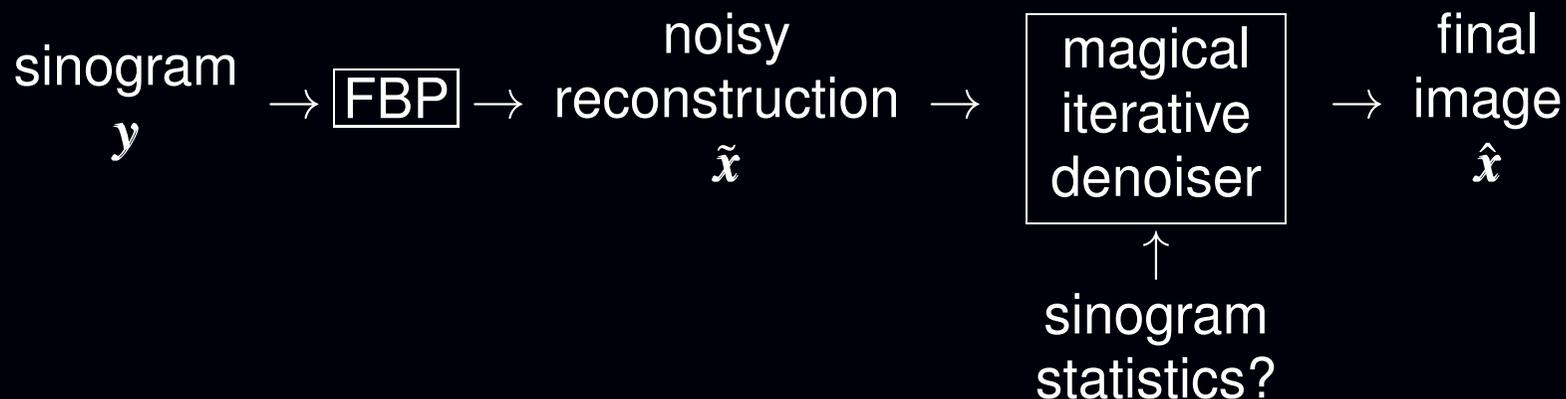
FBP



Denoised



- Image denoising methods “guided by data statistics”



- Image-domain methods are **fast** (thus very practical)
- ASIR? IRIS? ...
- The technical details are often a mystery...

Challenges:

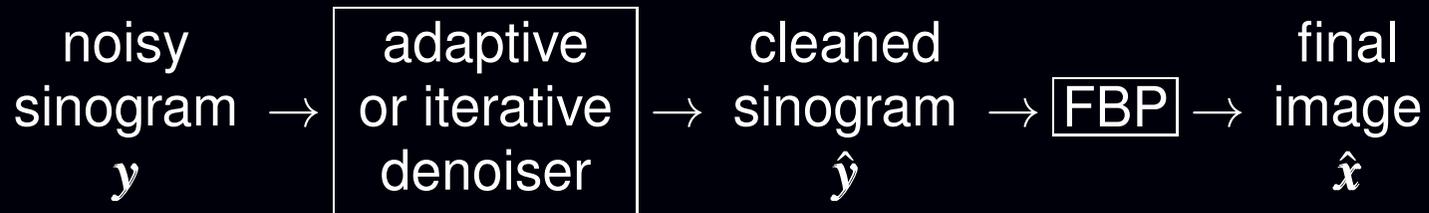
- FBP often does not use all data efficiently (*e.g.*, Parker weighting)
- Low-dose CT statistics most naturally expressed in sinogram domain

Several studies of potential dose reduction with image-domain methods:

- Hara *et al.*, AJR 193(3) 2009, 32-65 % **dose reduction**
- Silva *et al.*, AJR 194(1) 2010, 50-65 % **dose reduction**
- Leipsic *et al.*, AJR 195(3) 2010, 27 % **dose reduction**
- ...

“Statistical” methods: Sinogram domain

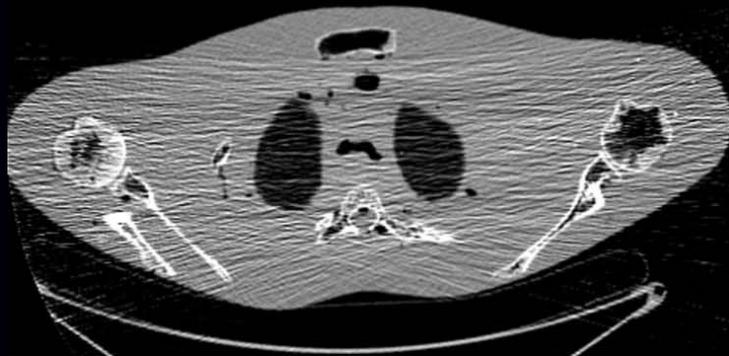
- Sinogram restoration methods



- Adaptive: J. Hsieh, Med. Phys., 1998; Kachelrieß, Med. Phys., 2001, ...
- Iterative: P. La Riviere, IEEE T-MI, 2000, 2005, 2006, 2008, ...
- Relatively **fast** even if iterative

Challenges:

- Limited denoising without resolution loss \implies modest **dose** reduction?
- Difficult to “preserve edges” in sinograms



FBP, 10 mA



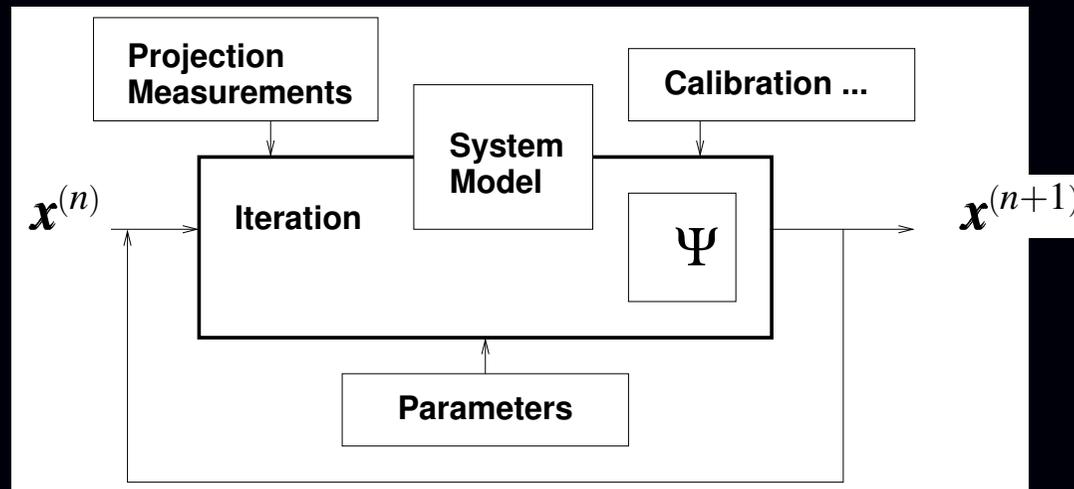
FBP from denoised sinogram

Wang *et al.*, T-MI, Oct. 2006, using PWLS-GS on sinogram

“Fully” (?) statistical image reconstruction

- Object model
- Physics/system model
- Statistical model
- Cost function (log-likelihood + regularization)
- Iterative algorithm for minimization

“Find the image \hat{x} that best fits the sinogram data y according to the physics model, the statistical model and prior information about the object”



- Repeatedly revisiting the sinogram data can use measurement statistics fully
- Repeatedly updating the image can exploit object properties
- \therefore greatest potential **dose reduction**, but repetition is expensive...

Sub-mSv example

3D helical X-ray CT scan of abdomen/pelvis:

100 kVp, 25-38 mA, 0.4 second rotation, 0.625 mm slice, 0.6 mSv.



FBP



ASIR



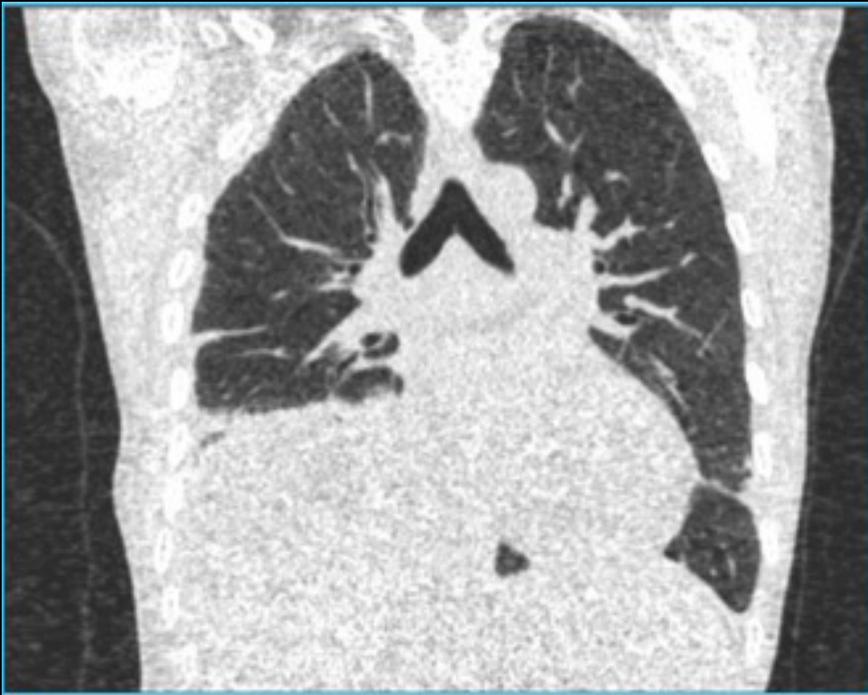
Statistical

MBIR example: Routine chest CT

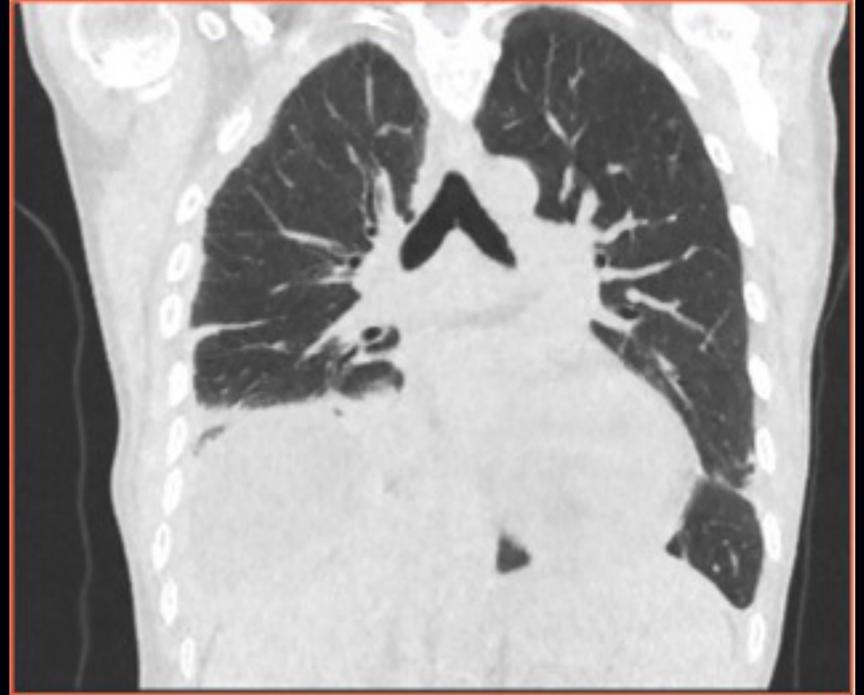
Helical chest CT study with dose = 0.09 mSv.

Typical CXR effective dose is about 0.06 mSv. Source: Health Physics Society.

<http://www.hps.org/publicinformation/ate/q2372.html>



FBP



MBIR

Veo (MBIR) images courtesy of Jiang Hsieh, GE Healthcare

History: Statistical reconstruction for PET

- Iterative method for emission tomography (Kuhl, 1963)
- FBP for PET (Chesler, 1971)
- Weighted least squares for 3D SPECT (Goitein, NIM, 1972)
- Richardson/Lucy iteration for image restoration (1972, 1974)
- Poisson likelihood (emission) (Rockmore and Macovski, TNS, 1976)
- Expectation-maximization (EM) algorithm (Shepp and Vardi, TMI, 1982)
- Regularized (aka Bayesian) Poisson emission reconstruction (Geman and McClure, ASA, 1985)
- Ordered-subsets EM (OSEM) algorithm (Hudson and Larkin, TMI, 1994)
- Commercial release of OSEM for PET scanners circa 1997

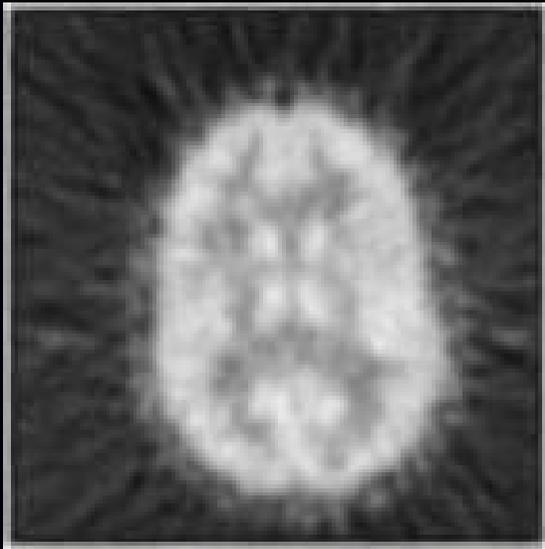
Today, most (all?) commercial PET systems include *unregularized* OSEM.

15 years between key EM paper (1982) and commercial adoption (1997)
(25 years if you count the R/L paper in 1972 which is the same as EM)

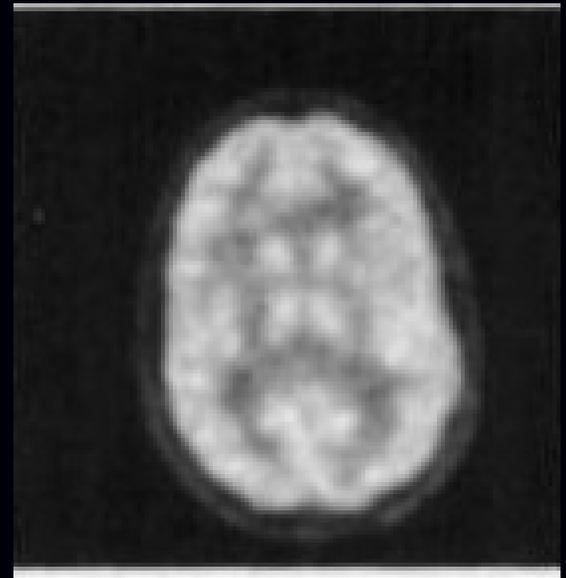
Key factors in PET

- OS algorithm accelerated convergence by order of magnitude
- Computers got faster (but problem size grew too)
- Key clinical validation papers?
- Key numerical observer studies?
- Nuclear medicine physicians grew accustomed to appearance of images reconstructed using statistical methods

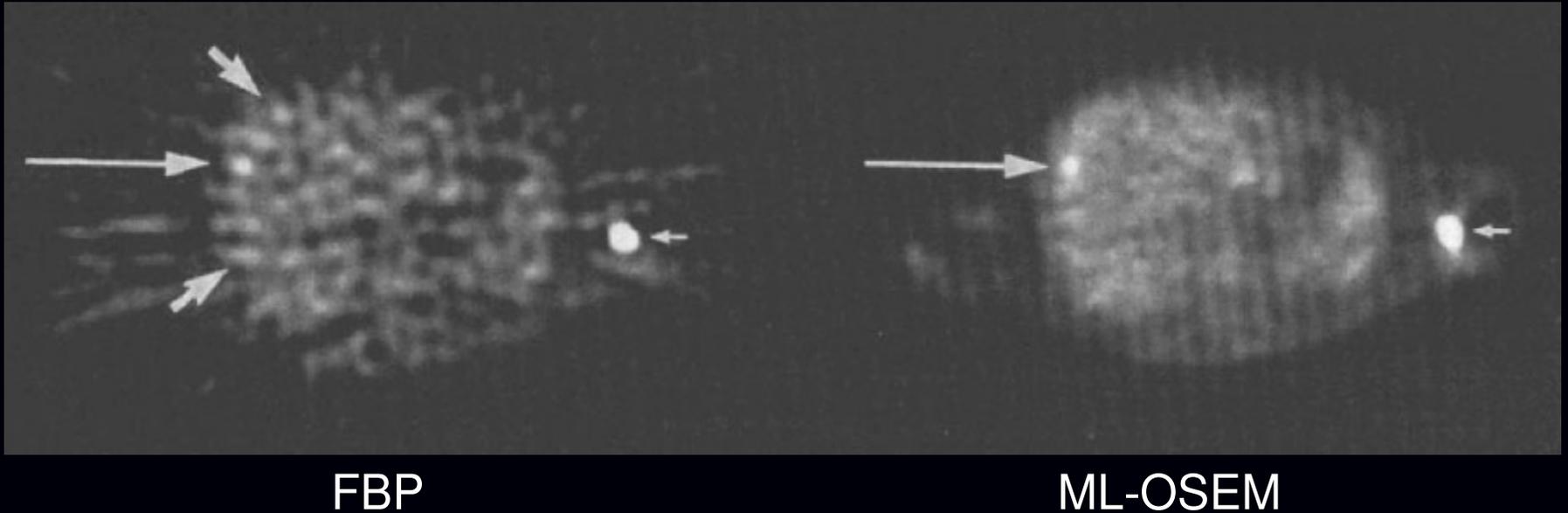
FBP:



ML-EM:



Whole-body PET example



Meikle *et al.*, 1994

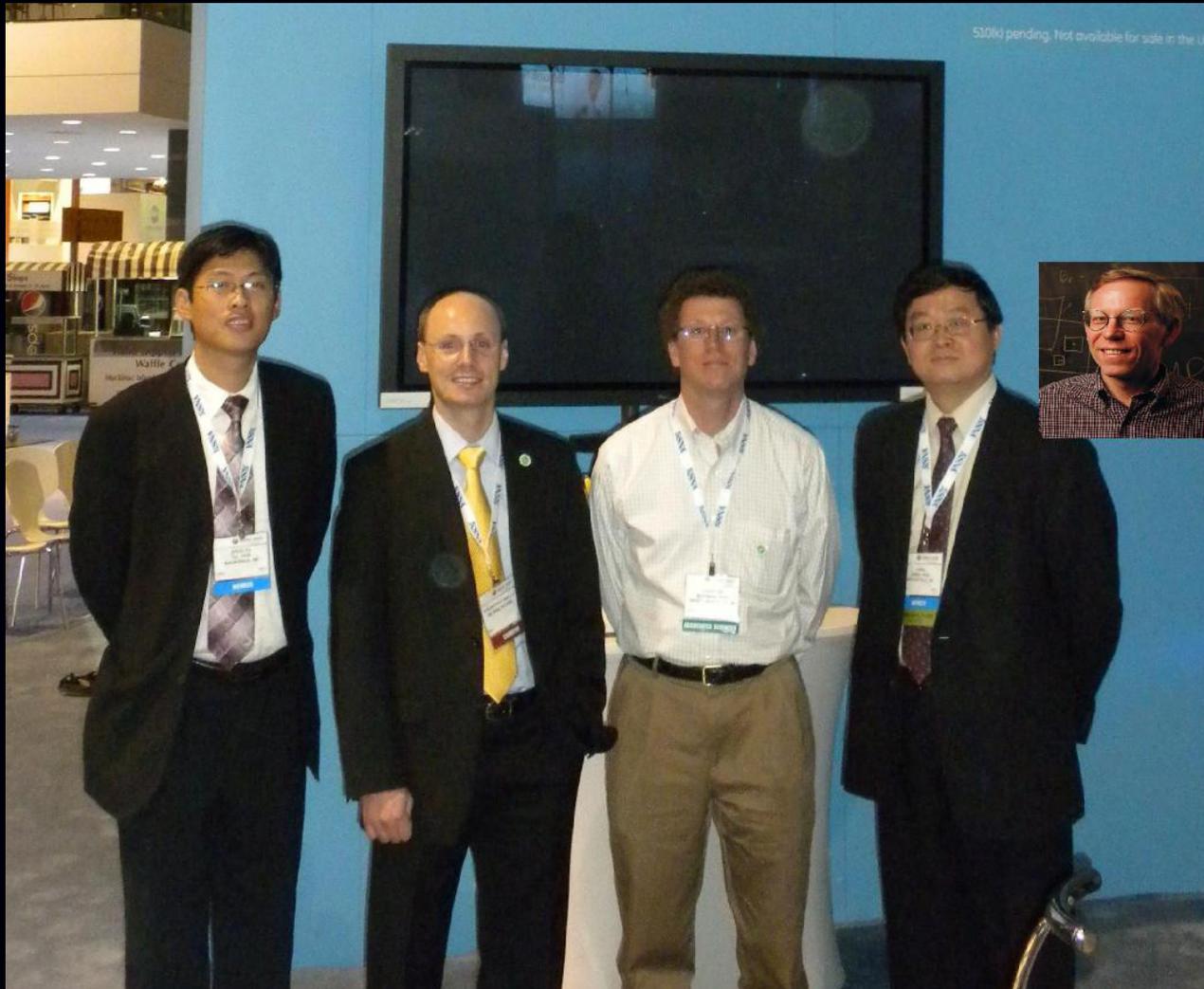
Key factor in PET: modeling measurement statistics

History: Statistical reconstruction for CT*

- Iterative method for X-ray CT (Hounsfield, 1968)
- ART for tomography (Gordon, Bender, Herman, JTB, 1970)
- ...
- Roughness regularized LS for tomography (Kashyap & Mittal, 1975)
- Poisson likelihood (transmission) (Rockmore and Macovski, TNS, 1977)
- EM algorithm for Poisson transmission (Lange and Carson, JCAT, 1984)
- Iterative coordinate descent (ICD) (Sauer and Bouman, T-SP, 1993)
- Ordered-subsets algorithms
(Manglos *et al.*, PMB 1995)
(Kamphuis & Beekman, T-MI, 1998)
(Erdoğan & Fessler, PMB, 1999)
- ...
- Commercial introduction of ICD for CT scanners circa 2010
- FDA 510(k) clearance of Veo Sep. 2011
(Prof. William Shuman of UW quoted in GE's press release.)

(* numerous omissions, including many denoising methods) 18

RSNA 2010



Zhou Yu, Jean-Baptiste Thibault, Charles Bouman, Jiang Hsieh, Ken Sauer

Five Choices for Statistical Image Reconstruction

1. Object model
2. System physical model
3. Measurement **statistical model**
4. Cost function: data-mismatch and **regularization**
5. Algorithm / initialization

No perfect choices - one can critique all approaches!

Historically these choices are often left implicit in publications, but being explicit facilitates reproducibility.

Next: overview of each choice, focusing on how they may affect dose.

Choice 1. Object Parameterization

Finite measurements: $\{y_i\}_{i=1}^M$.

Continuous object: $f(\vec{r}) = \mu(\vec{r})$.

“All models are wrong but some models are useful.”

Linear *series expansion* approach. Represent $f(\vec{r})$ by $\mathbf{x} = (x_1, \dots, x_N)$ where

$$f(\vec{r}) \approx \tilde{f}(\vec{r}) = \sum_{j=1}^N x_j b_j(\vec{r}) \leftarrow \text{“basis functions”}$$

Reconstruction problem becomes “discrete-discrete:” estimate \mathbf{x} from \mathbf{y}

Numerous basis functions in literature. Two primary contenders:

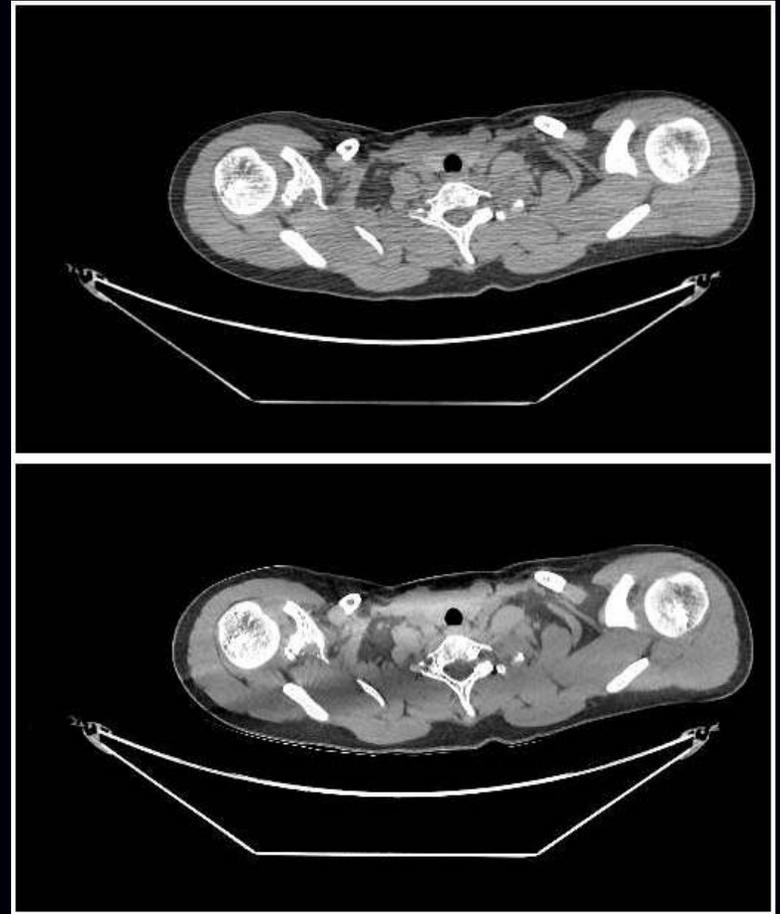
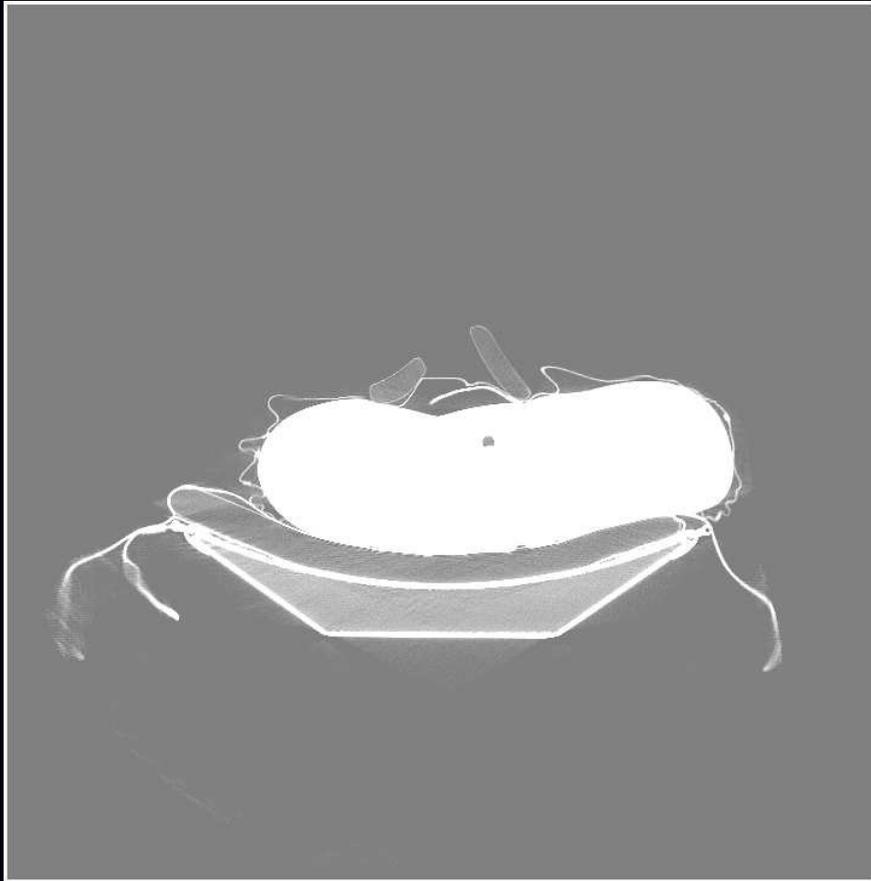
- voxels
- blobs (Kaiser-Bessel functions)
 - + Blobs are approximately band-limited (reduced aliasing?)
 - Blobs have larger footprints, increasing computation.

Open question: how small should the voxels be?

One practical compromise: wide FOV coarse-grid reconstruction followed by fine-grid refinement over ROI, *e.g.*, Ziegler *et al.*, Med. Phys., Apr. 2008

Global reconstruction: An inconvenient truth

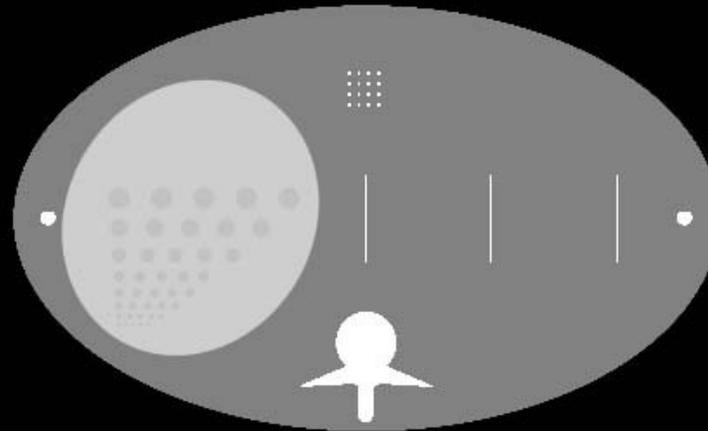
70-cm FOV reconstruction



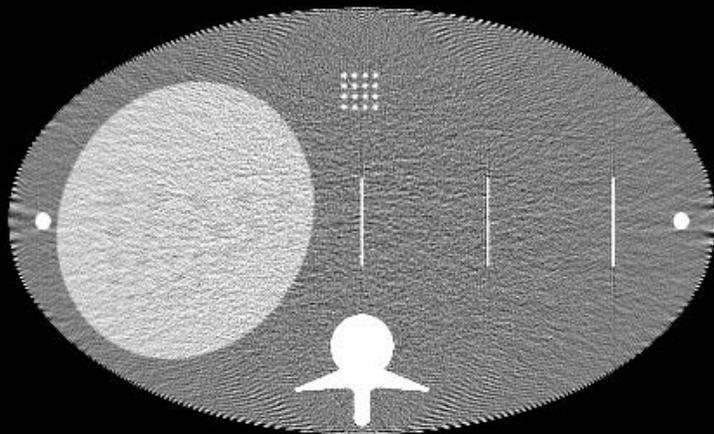
Thibault *et al.*, Fully3D, 2007

For a statistical approach to interior tomography, see Xu *et al.*, IEEE T-MI, May 2011.

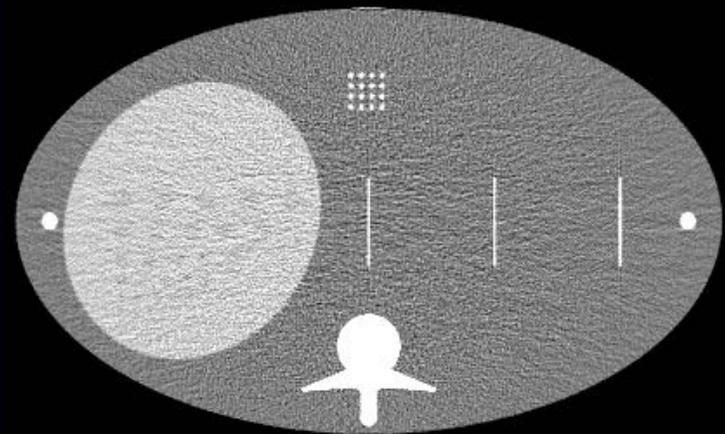
Voxel size matters?



digital phantom



512^2 grid



1024^2 grid

Unregularized OS reconstructions. Zbijewski & Beekman, PMB, Jan. 2004

Choice 2. System model / Physics model

- scan geometry
- source intensity I_0
 - spatial variations (air scan)
 - intensity fluctuations
- resolution effects
 - finite detector size / detector spatial response
 - finite X-ray spot size / anode angulation
 - detector afterglow / gantry rotation
- spectral effects
 - X-ray source spectrum
 - bowtie filters
 - detector spectra response
- scatter
- ...

Challenges / trade-offs

- computation time
- accuracy/artifacts/resolution/contrast
- dose?

Detector size modeling matters

From (De Man and Basu, PMB, Jun. 2004)

MLTR of rabbit heart

Ray-driven (idealized point detector)



Distance-driven (models finite detector width)



Forward- / Back-projector “Pairs”

Typically iterative algorithms require two key steps.

- **forward projection** (image domain to projection domain):

$$\bar{\mathbf{y}} = \mathbf{A}\mathbf{x}, \quad \bar{y}_i = \sum_{j=1}^N a_{ij}x_j = [\mathbf{A}\mathbf{x}]_i$$

- **backprojection** (projection domain to image domain):

$$\mathbf{z} = \mathbf{A}'\mathbf{y}, \quad z_j = \sum_{i=1}^M a_{ij}y_i$$

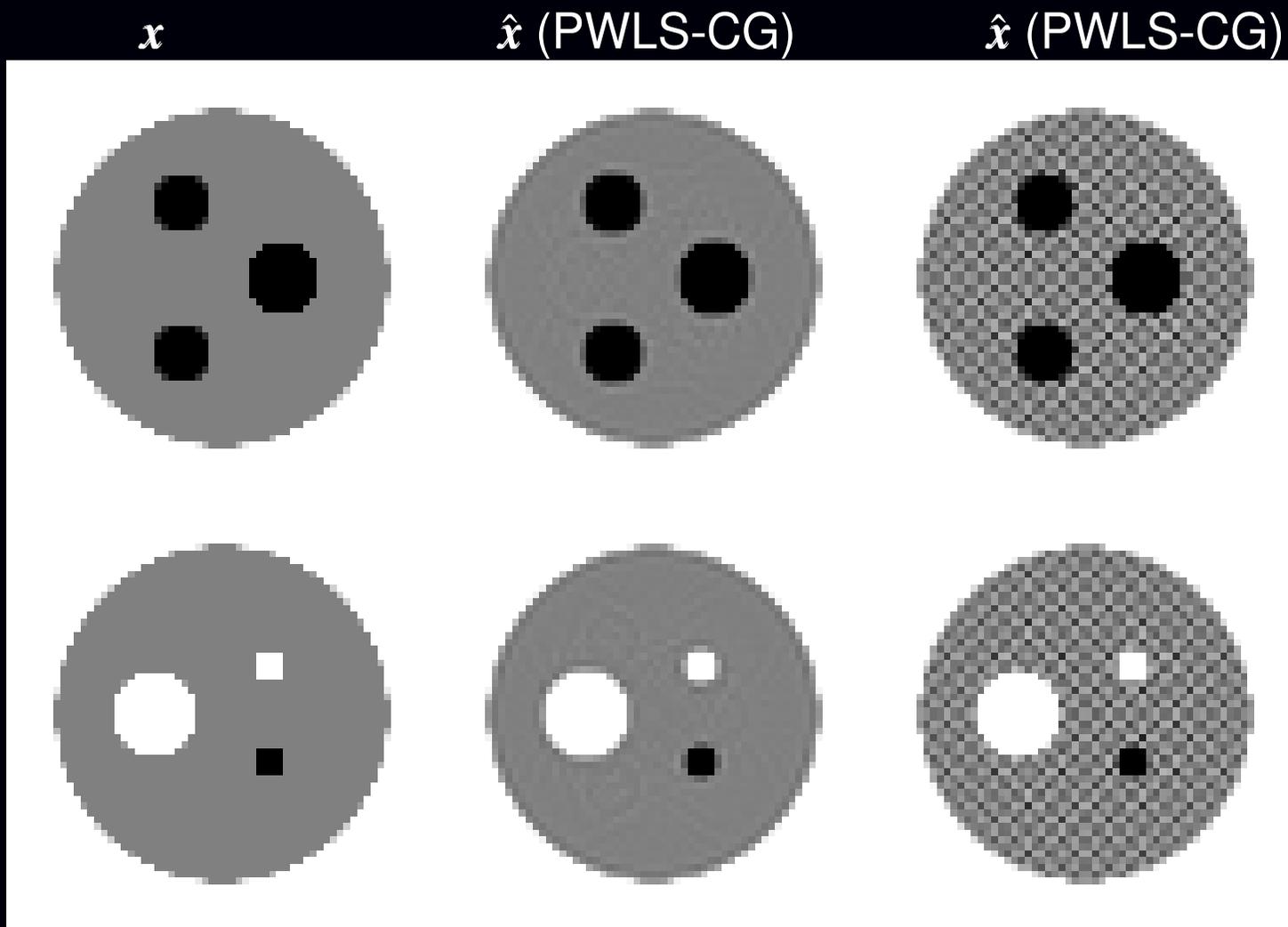
The term “forward/backprojection pair” often refers to some implicit choices for the object basis and the system model.

Sometimes $\mathbf{A}'\mathbf{y}$ is implemented as $\mathbf{B}\mathbf{y}$ for some “backprojector” $\mathbf{B} \neq \mathbf{A}'$. Especially in SPECT and sometimes in PET and CT.

Least-squares solutions (for example):

$$\hat{\mathbf{x}} = \arg \min_x \|\mathbf{y} - \mathbf{A}\mathbf{x}\|^2 = [\mathbf{A}'\mathbf{A}]^{-1} \mathbf{A}'\mathbf{y} \neq [\mathbf{B}\mathbf{A}]^{-1} \mathbf{B}\mathbf{y}$$

Mismatched Backprojector $B \neq A'$



Matched

Mismatched

cf. SPECT/PET reconstruction – usually unregularized

Choice 3. Statistical Model

The physical model describes measurement mean, *e.g.*, for a monoenergetic X-ray source and ignoring scatter etc.:

$$\bar{I}_i = I_0 e^{-\sum_{j=1}^N a_{ij}x_j}.$$

The raw noisy measurements $\{I_i\}$ are distributed around those means. Statistical reconstruction methods require a model for that distribution.

Challenges / Trade offs: using more accurate statistical models

- *may* lead to less noisy images
- may incur additional computation
- may involve higher algorithm complexity.

CT measurement statistics are very complicated, particularly at low doses.

- incident photon flux variations (Poisson)
- X-ray photon absorption/scattering (Bernoulli)
- energy-dependent light production in scintillator (?)
- shot noise in photodiodes (Poisson?)
- electronic noise in readout electronics (Gaussian?)

Whiting, SPIE 4682, 2002; Lasio *et al.*, PMB, 2007; Massoumzadeh *et al.*, PMB 2009

- Inaccessibility of raw sinogram data

To log() or not to log() – That is the question

Models for “raw” data I_i (before logarithm)

- **compound Poisson** (complicated) Whiting, SPIE 4682, 2002;
Elbakri & Fessler, SPIE 5032, 2003; Lasio *et al.*, PMB, Apr. 2007

- **Poisson + Gaussian** (photon variability and electronic readout noise):

$$I_i \sim \text{Poisson}\{\bar{I}_i\} + N(0, \sigma^2)$$

Snyder *et al.*, JOSAA, May 1993 & Feb. 1995 .

- **Shifted Poisson** approximation (matches first two moments):

$$\tilde{I}_i \triangleq [I_i + \sigma^2]_+ \sim \text{Poisson}\{\bar{I}_i + \sigma^2\}$$

Yavuz & Fessler, MIA, Dec. 1998

- **Ordinary Poisson** (ignore electronic noise):

$$I_i \sim \text{Poisson}\{\bar{I}_i\}$$

Rockmore and Macovski, TNS, Jun. 1977; Lange and Carson, JCAT, Apr. 1984

- Photon-counting detectors would simplify statistical modeling

All are somewhat complicated by the **nonlinearity** of the physics: $\bar{I}_i = e^{-[Ax]_i}$

After taking the log()

Taking the log leads to a simpler **linear** model (ignoring beam hardening):

$$y_i \triangleq -\log\left(\frac{I_i}{I_0}\right) \approx [\mathbf{Ax}]_i + \varepsilon_i$$

Drawbacks:

- Undefined if $I_i \leq 0$ (due to electronic noise); bad for very **low-dose** scans
- It is *biased* (by Jensen's inequality): $E[y_i] \geq -\log(\bar{I}_i/I_0) = [\mathbf{Ax}]_i$
- Exact distribution of log-domain noise ε_i is intractable.

Practical approach: assume Gaussian noise model: $\varepsilon_i \sim N(0, \sigma_i^2)$

Options for modeling noise variance $\sigma_i^2 = \text{Var}\{\varepsilon_i\}$

- consider both Poisson and Gaussian noise effects: $\sigma_i^2 = \frac{\bar{I}_i + \sigma^2}{\bar{I}_i^2}$
(Thibault *et al.*, SPIE 6065, 2006)
- consider just Poisson effect: $\sigma_i^2 = \frac{1}{\bar{I}_i}$ (Sauer & Bouman, T-SP, Feb. 1993)
- pretend it is white noise: $\sigma_i^2 = \sigma_0^2$
- ignore noise altogether and “solve” $\mathbf{y} = \mathbf{Ax}$

Whether using pre-log data is better than post-log data is an open question, especially for very **low-dose** scans (*cf.* experience with PET rod scans).

Choice 4. Cost Functions

Components:

- 4.1 *Data-mismatch* term
- 4.2 *Regularization* term (and regularization parameter β)
- 4.3 *Constraints* (e.g., nonnegativity: minor effect on noise / **dose**)

Reconstruct image $\hat{\mathbf{x}}$ by finding minimizer of a cost function:

$$\hat{\mathbf{x}} \triangleq \underbrace{\arg \min_{\mathbf{x} \geq 0}}_{\text{Constraints}} \Psi(\mathbf{x})$$

$$\Psi(\mathbf{x}) = \text{DataMismatch}(\mathbf{y}, \mathbf{Ax}) + \beta \text{Regularizer}(\mathbf{x})$$

Forcing too much “data fit” alone would give noisy images.

Equivalent to a Bayesian MAP (maximum *a posteriori*) estimator.

Distinguishes “statistical methods” from “algebraic methods” for “ $\mathbf{y} = \mathbf{Ax}$.”

Such optimization-based formulation appears to be key to **low-dose** CT.
Theoretically optimizes bias-variance trade-off (Eldar, IEEE T-SP, Jul. 2004).

Choice 4.1: Data-Mismatch Term

Standard choice is the negative log-likelihood of statistical model:

$$\text{DataMismatch} = -L(\mathbf{x}; \mathbf{y}) = -\log p(\mathbf{y}|\mathbf{x}) = \sum_{i=1}^M -\log p(y_i|\mathbf{x}).$$

- For pre-log data \mathbf{I} with **shifted Poisson** model:

$$-L(\mathbf{x}; \mathbf{I}) = \sum_{i=1}^M (\bar{I}_i + \sigma^2) - [I_i + \sigma^2]_+ \log(\bar{I}_i + \sigma^2), \quad \bar{I}_i = I_0 e^{-[\mathbf{Ax}]_i}$$

This can be non-convex if $\sigma^2 > 0$;

it is convex if we ignore electronic noise $\sigma^2 = 0$. Trade-off ...

- For post-log data \mathbf{y} with **Gaussian** model:

$$-L(\mathbf{x}; \mathbf{y}) = \sum_{i=1}^M w_i \frac{1}{2} (y_i - [\mathbf{Ax}]_i)^2 = \frac{1}{2} (\mathbf{y} - \mathbf{Ax})' \mathbf{W} (\mathbf{y} - \mathbf{Ax}), \quad w_i = 1/\sigma_i^2$$

This is a kind of (data-based) weighted least squares (**WLS**).

It is always convex in \mathbf{x} . Quadratic functions are “easy” to minimize.

- ...

- Effect on **dose** is related to statistical model accuracy

Choice 4.2: Regularization

How to control noise due to ill-conditioning in tomography?

Perhaps the most important factor influencing “how low (dose) can we go”

Noise-control methods (used in clinical PET reconstruction today):

- Stop an unregularized algorithm before convergence
- Over-iterate an unregularized algorithm then post-filter

Other possible “simple” solutions:

- Modify the raw data (pre-filter / denoise)
- Filter between iterations
- ...

Appeal:

- simple / familiar
- filter parameters have intuitive units (e.g., FWHM), unlike a regularization parameter β
- Changing a post-filter does not require re-iterating, unlike changing a regularization parameter β

Regularization options

Options for regularizer $R(\mathbf{x})$ in increasing complexity:

- quadratic roughness
- convex, non-quadratic roughness
- non-convex roughness
- total variation
- convex sparsity
- non-convex sparsity

Challenges

- Reducing noise without degrading spatial resolution
- Balancing regularization strength between and within slices
- Parameter selection
- Computational complexity (voxels have 26 immediate neighbors in 3D)
- Preserving “familiar” noise texture
- Optimizing clinical task performance

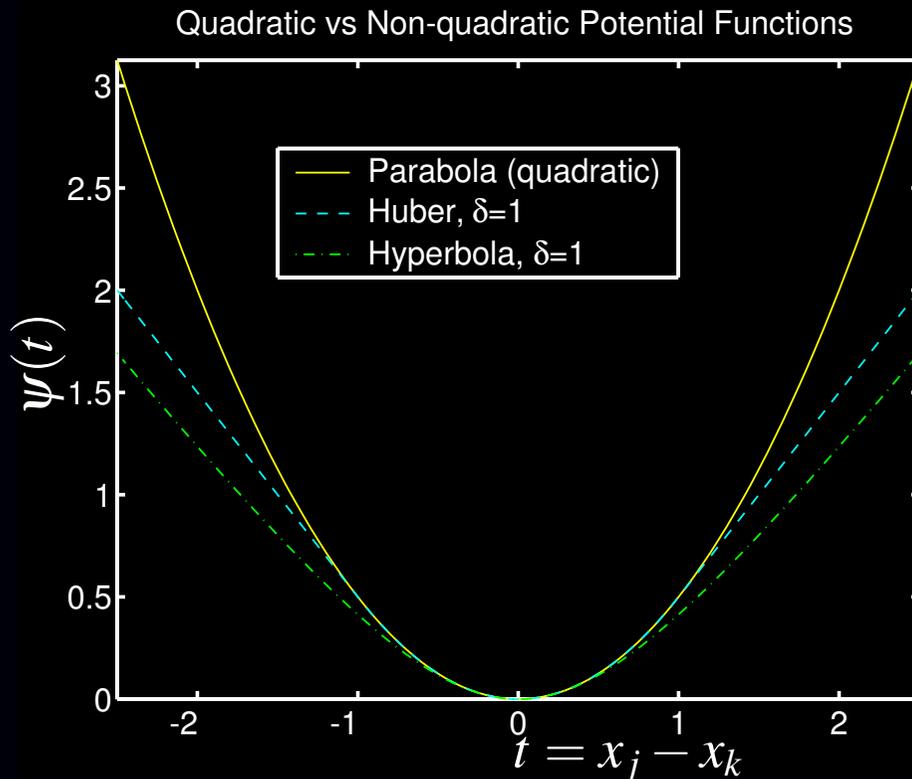
Many open questions...

Which regularization method can enable the **lowest-dose** scans?

Roughness Penalty Functions

$$R(\mathbf{x}) = \sum_{j=1}^N \frac{1}{2} \sum_{k \in \mathcal{N}_j} \psi(x_j - x_k)$$

- $\mathcal{N}_j \triangleq$ *neighborhood* of j th pixel
(e.g., left, right, up, down in 2D; 26 neighbors in 3D)
- ψ called the *potential function*



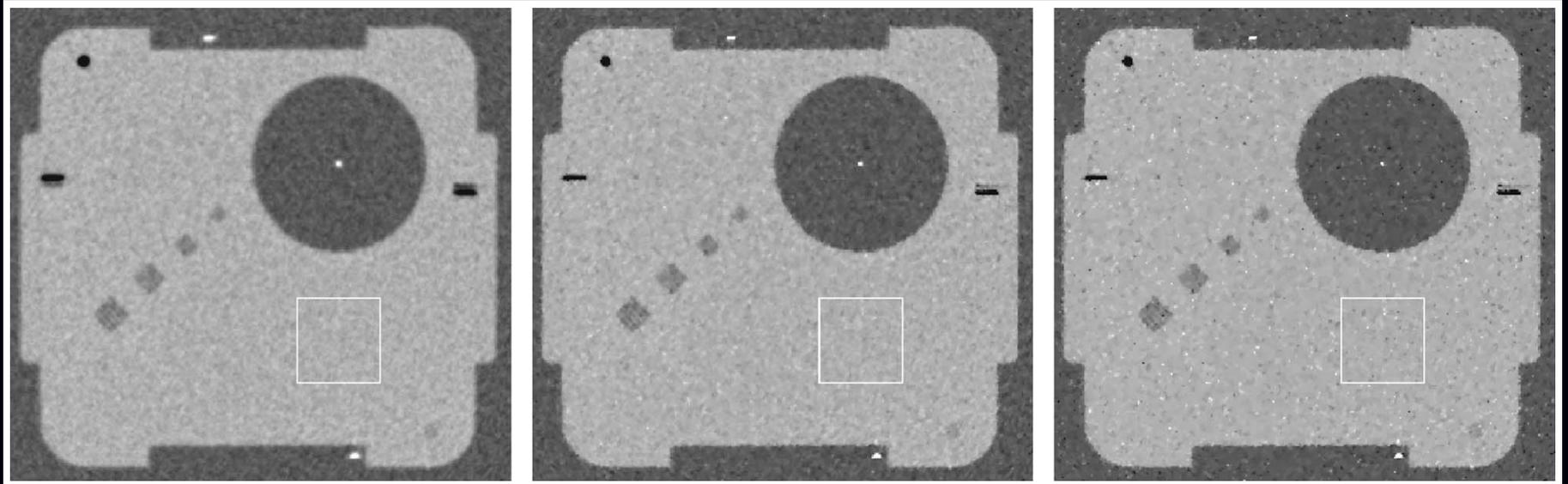
quadratic: $\psi(t) = t^2$
hyperbola: $\psi(t) = \sqrt{1 + (t/\delta)^2}$
(edge preservation)

Regularization parameters: Dramatic effects on IQ

“ q generalized gaussian” potential function with tuning parameters: β, δ, p, q :

$$\beta \psi(t) = \beta \frac{\frac{1}{2} |t|^p}{1 + |t/\delta|^{p-q}}$$

(Thibault *et al.*, Med. Phys., Nov. 2007)



$p = q = 2$

$p = 2, q = 1.2, \delta = 10$ HU

$p = q = 1.1$

noise: 11.1

10.9

10.8

(#lp/cm): 4.2

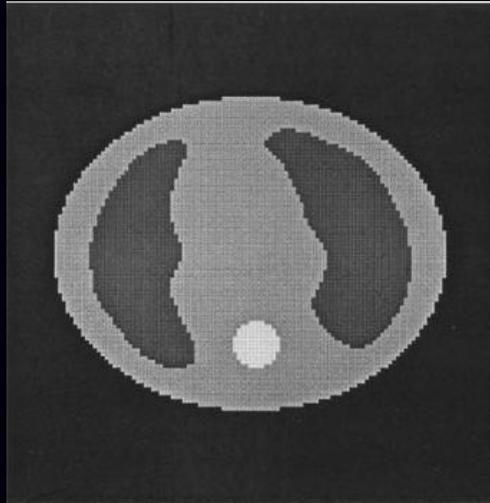
7.2

8.2

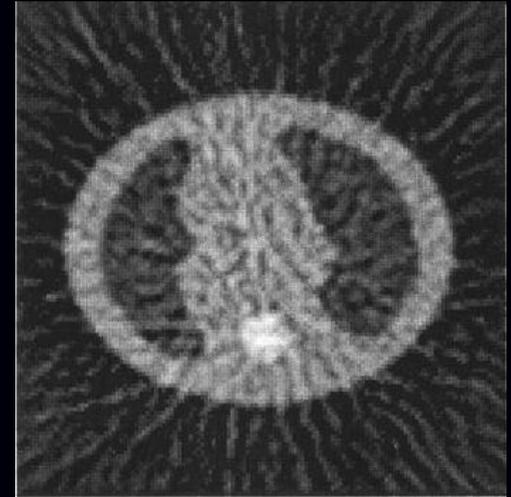
Which parameter choice enables the **lowest dose** scan?

Piecewise constant phantoms

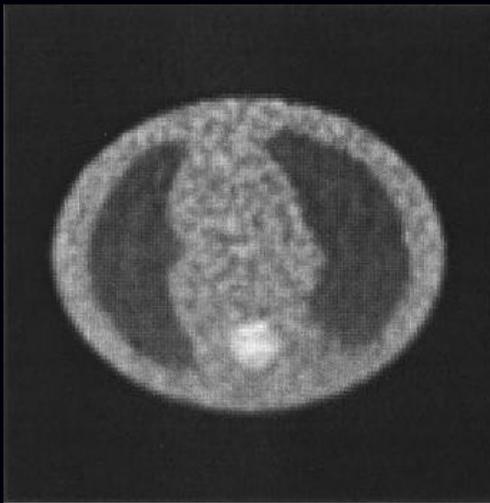
Phantom:



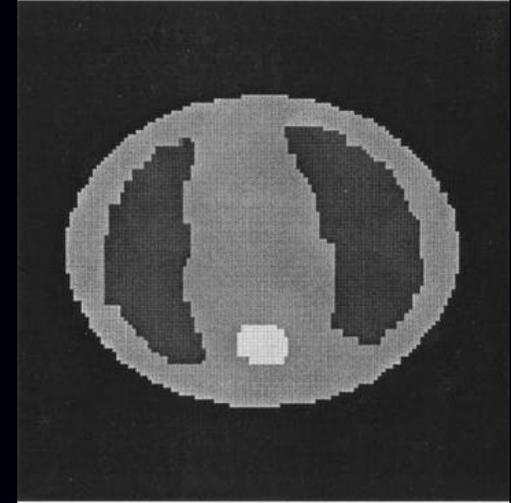
FBP:



MLEM:



MAP:



Lee *et al.*, IEEE T-NS, 2002, 300K counts
non-convex “broken parabola” potential function and deterministic annealing

Summary of statistical image reconstruction choices

1. Object parameterization
2. System physical model
3. Measurement statistical model
4. Cost function: data-mismatch / regularization / constraints

Reconstruction Method \triangleq Models + Cost Function + Algorithm

5. Minimization algorithms: $\hat{x} = \underset{x}{\arg \min} \Psi(x)$
 - The minimization algorithm has *no affect on image quality / dose* if we iterate “until convergence.”
 - For convergent algorithms, IQ determined entirely by cost function Ψ including the models within it.
 - What happens we stop iterating “before convergence?” Affects **dose**? (Depends on algorithm and initial image...)
 - Finding fast algorithms for **arg min** is key to ubiquitous low-dose CT. *e.g.*, alternating direction method of multipliers (ADMM) (Ramani & Fessler, IEEE T-MI, Mar. 2012)

Summary: Factors that affect dose reduction

In conjectured order from most important to least:

1. Regularizer
2. Statistical model / data-mismatch term
3. System model
4. Object model / non-negativity constraint
5. Iterative minimization algorithm

Other considerations that affect dose reduction

- 2D versus 3D reconstruction
 - 8 immediate neighbors in 2D versus 26 neighbors in 3D
 - transaxial versus axial relationships
- axial versus helical scans
- angular sampling: fine versus sparse
- dual energy / spectral CT versus single kVp

Recent dose figures for statistical image reconstruction

Yadava *et al.*, AAPM 2010, AAPM 2011

“average-probability-of-detection and average-detection-score of full dose FBP and 1/4th dose Veo [MBIR] are comparable.”

Cohen *et al.*, AAPM 2011

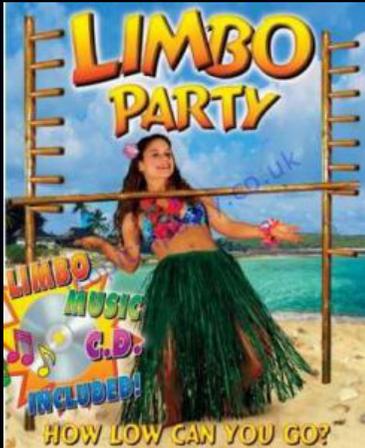
[Phantom] “measurement differences between full dose FBP and 1/4th dose Veo were found to be statistically insignificant, indicating similar image quality.”

Katsura *et al.*, Eur. Radiol. Aug. 2012

(hot off the press)

Compared FBP, ASIR, and “MBIR” (with no almost description);
concluded MBIR can work with “80% less radiation.”

How low (dose) can you go?

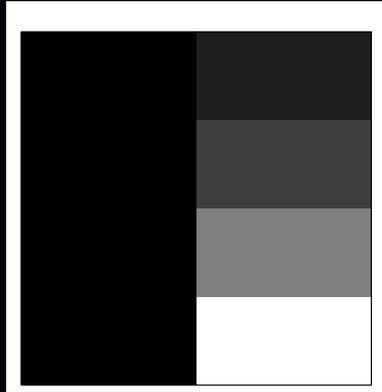


<http://laidoffinnyc.wordpress.com/2009/03/04/>

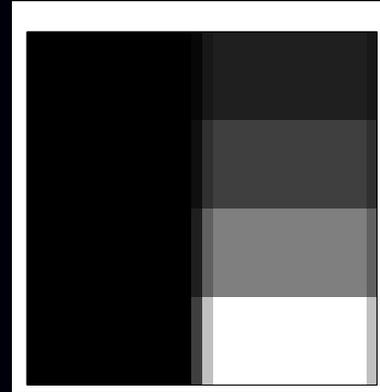
- Depends on where you start
- Depends on many reconstruction method choices
- all of which affect IQ
(which is harder to assess for nonlinear reconstruction methods)
- Conjecture: sub-mSv exams are achievable

Contrast-dependent edge resolution: 1D

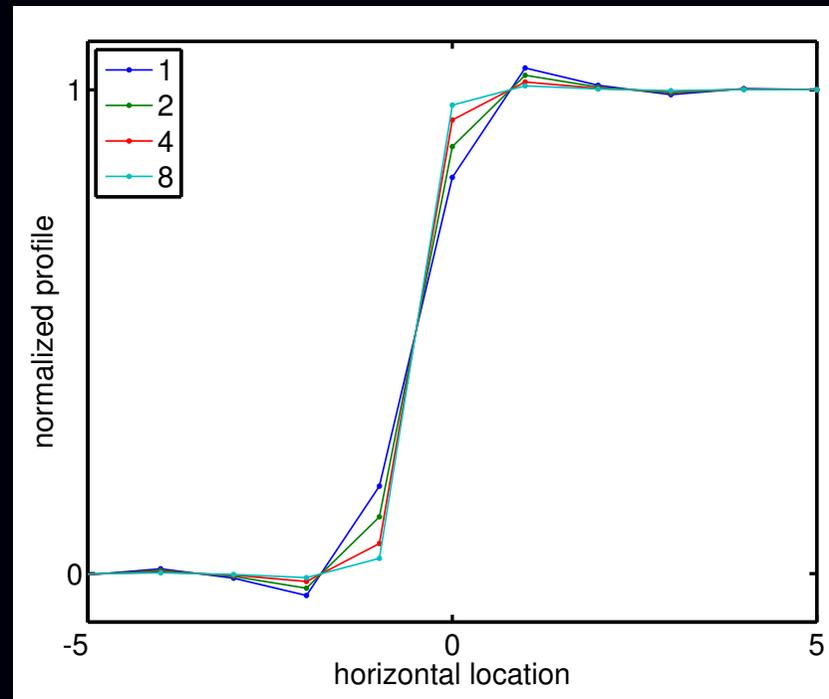
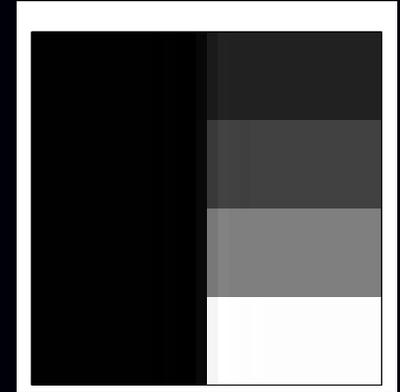
Orig:



Noiseless
blurry
image:

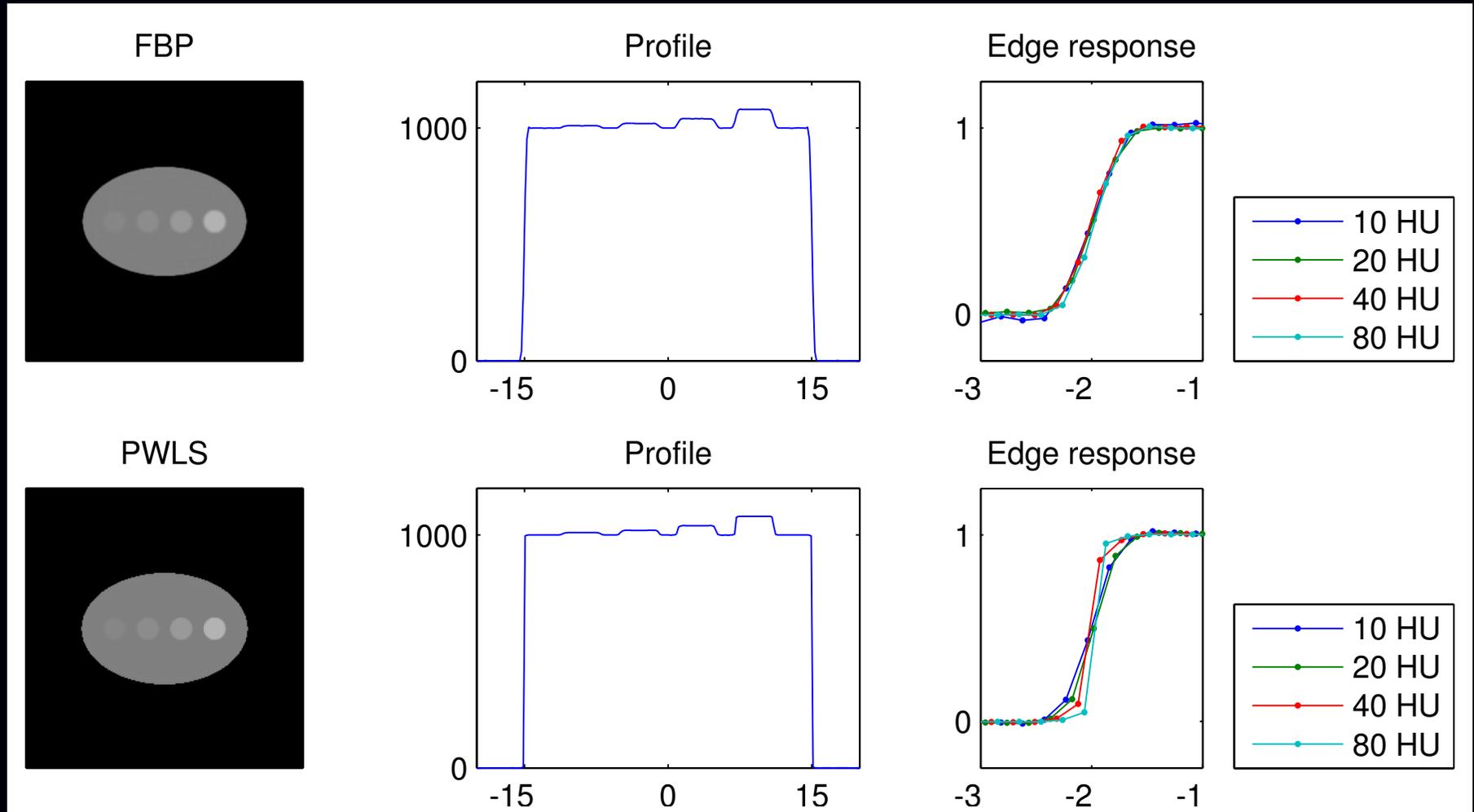


Restored
image
using
PWLS
 $\delta = 1$:



Challenge: *Shape of edge response depends on contrast when “preserving edges.”*

Contrast-dependent edge resolution: 2D CT



Challenge:

Shape of edge response depends on contrast for edge-preserving regularization.

Assessing image quality

Challenges:

- Resolution (PSF, edge response, MTF)
- Noise (predictions)
- Task-based performance measures
Known-location versus unknown-location tasks
- ...

“How low can the dose go” – quite challenging to answer

Some open problems in statistical image reconstruction

- **Modeling**
 - Statistical modeling for very low-dose CT
 - Resolution effects
 - Spectral CT
 - Object motion
 - Dynamic imaging (perfusion CT)
- **Parameter selection / performance characterization**
 - Performance prediction for nonquadratic regularization
 - Effect of nonquadratic regularization on detection tasks
 - Choice of regularization parameters for nonquadratic regularization
- **Algorithms**
 - optimization algorithm design
 - software/hardware implementation
 - Moore's law alone will not suffice
(dual energy, dual source, motion, dynamic, smaller voxels ...)
- **Clinical evaluation**
- ...

Many research opportunities to aid this CT revolution...

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