Basics of CT Image Reconstruction

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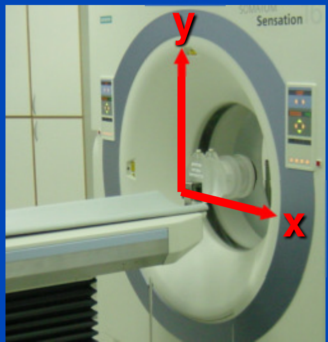
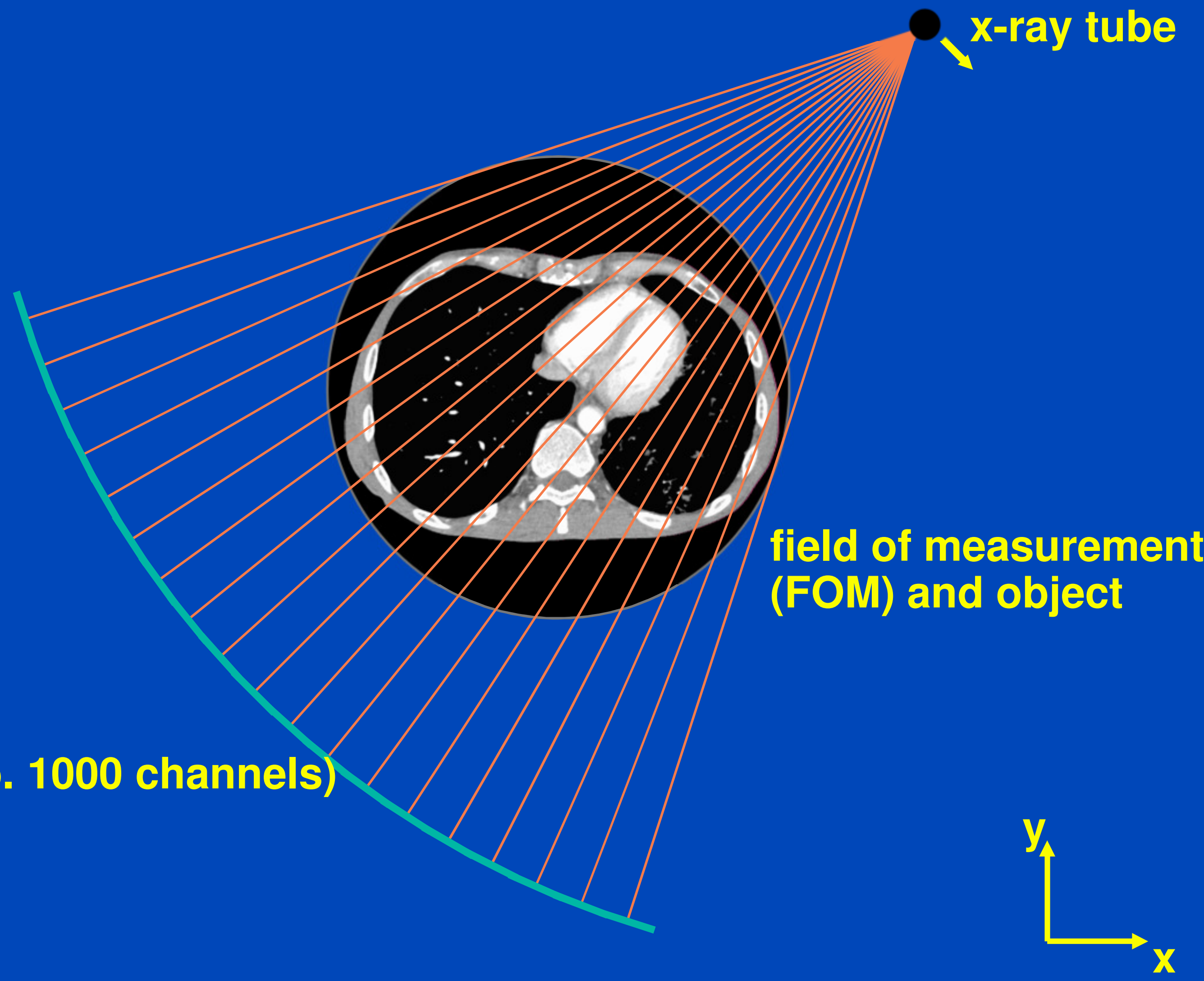
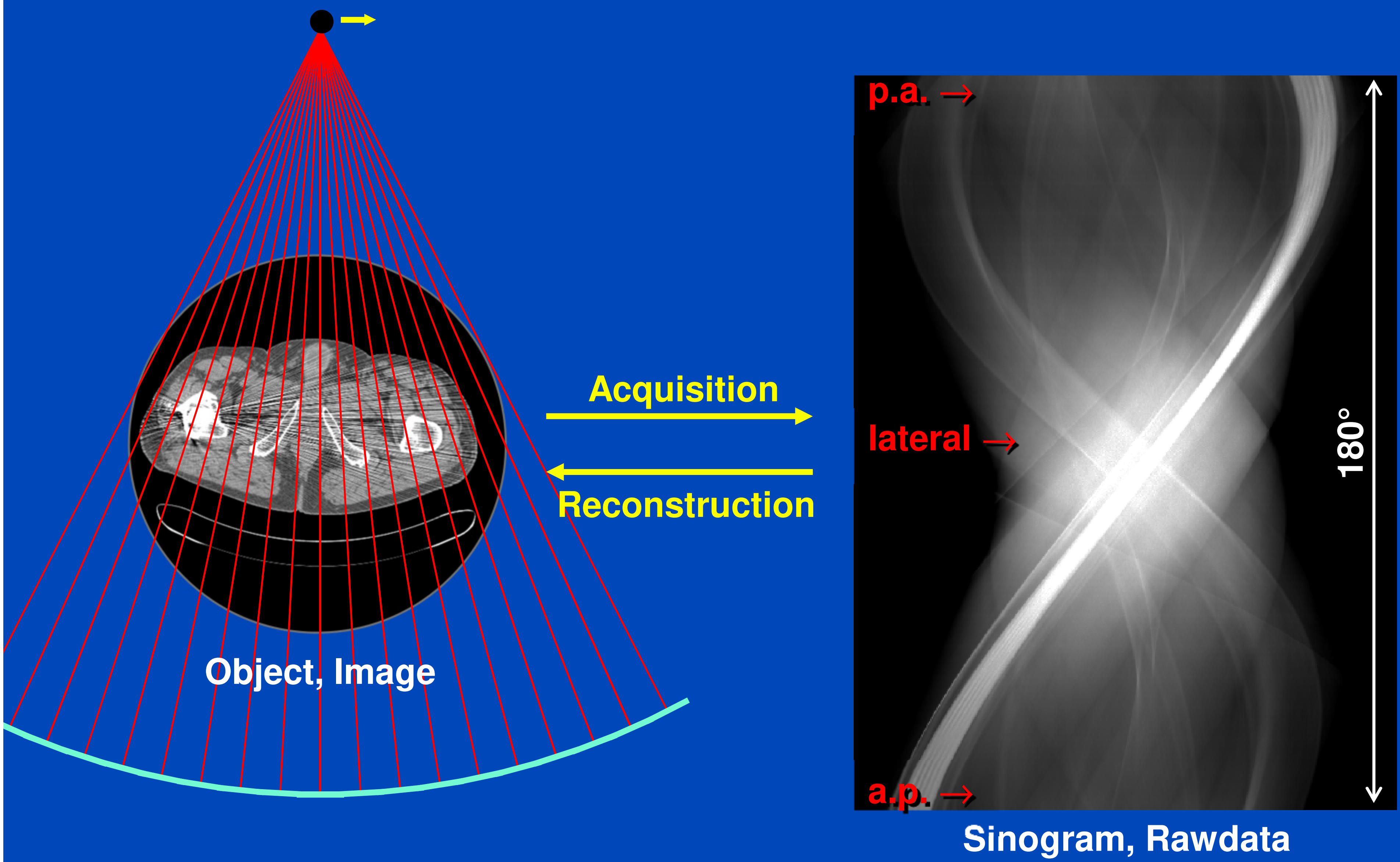
DEUTSCHES KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

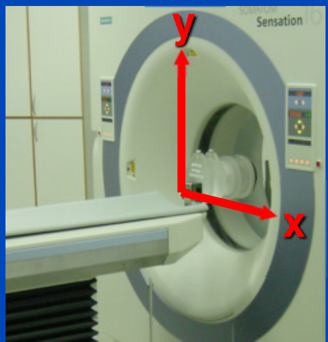
Fan-Beam Geometry
(transaxial / in-plane / x-y-plane)

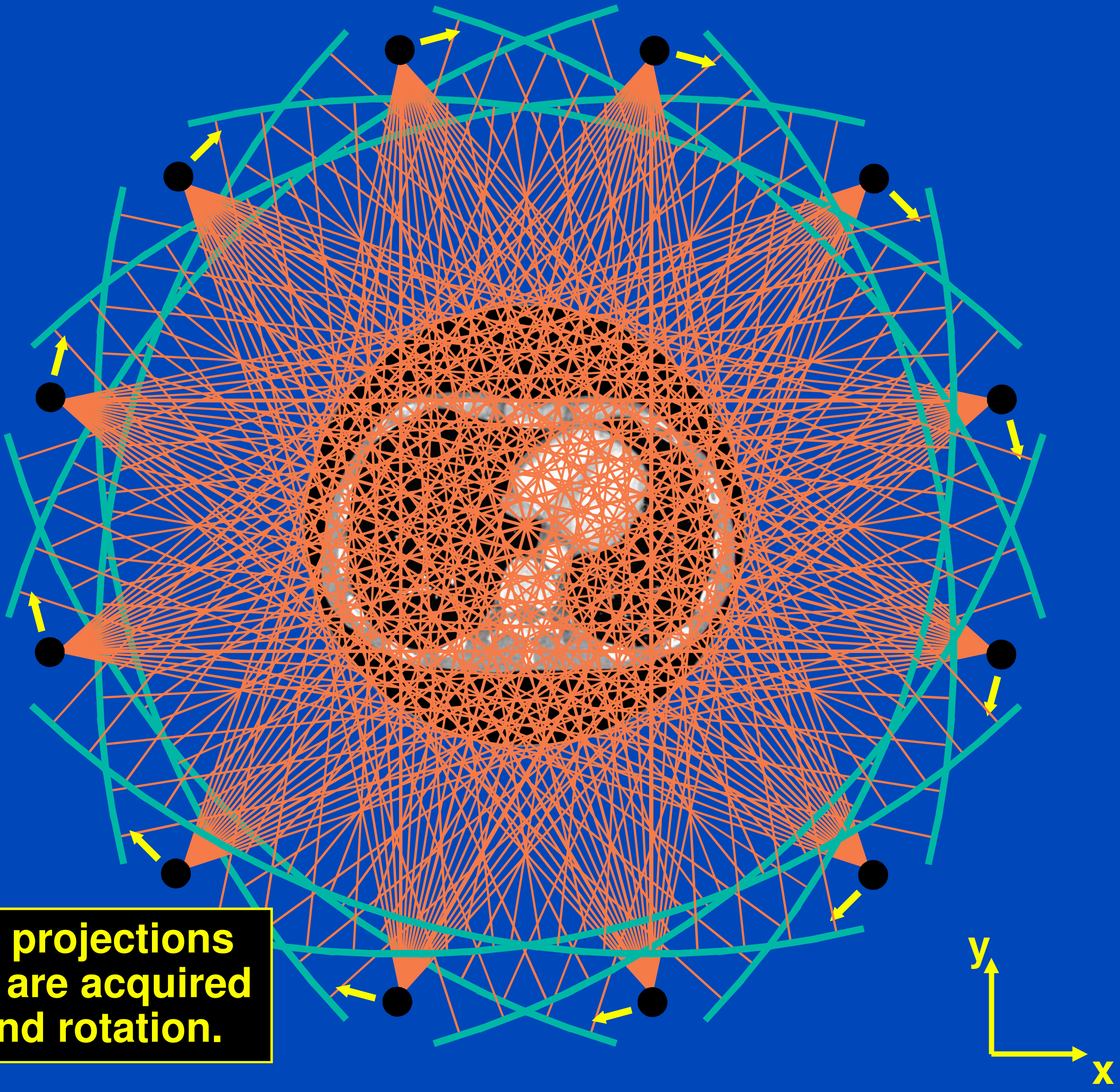






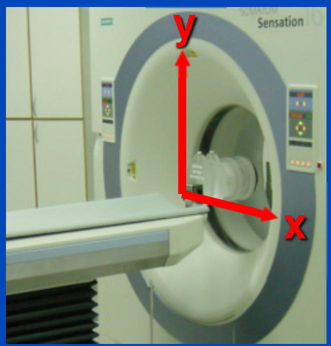
Acquisition
Reconstruction
Object, Image
p.a. →
lateral →
a.p. →
180°
Sinogram, Rawdata

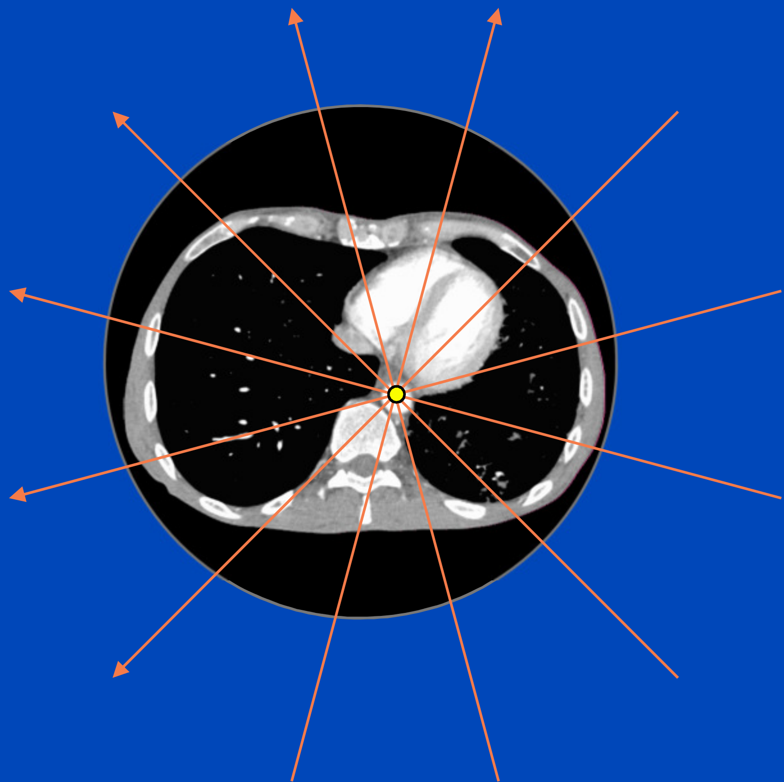




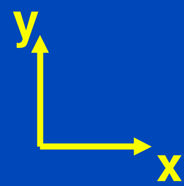
In the order of 1000 projections with 1000 channels are acquired per detector slice and rotation.

Data Completeness





Each object point must be viewed by an angular interval of 180° or more. Otherwise image reconstruction is not possible.



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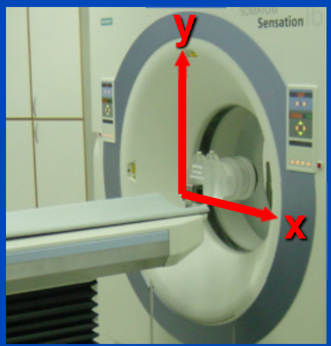
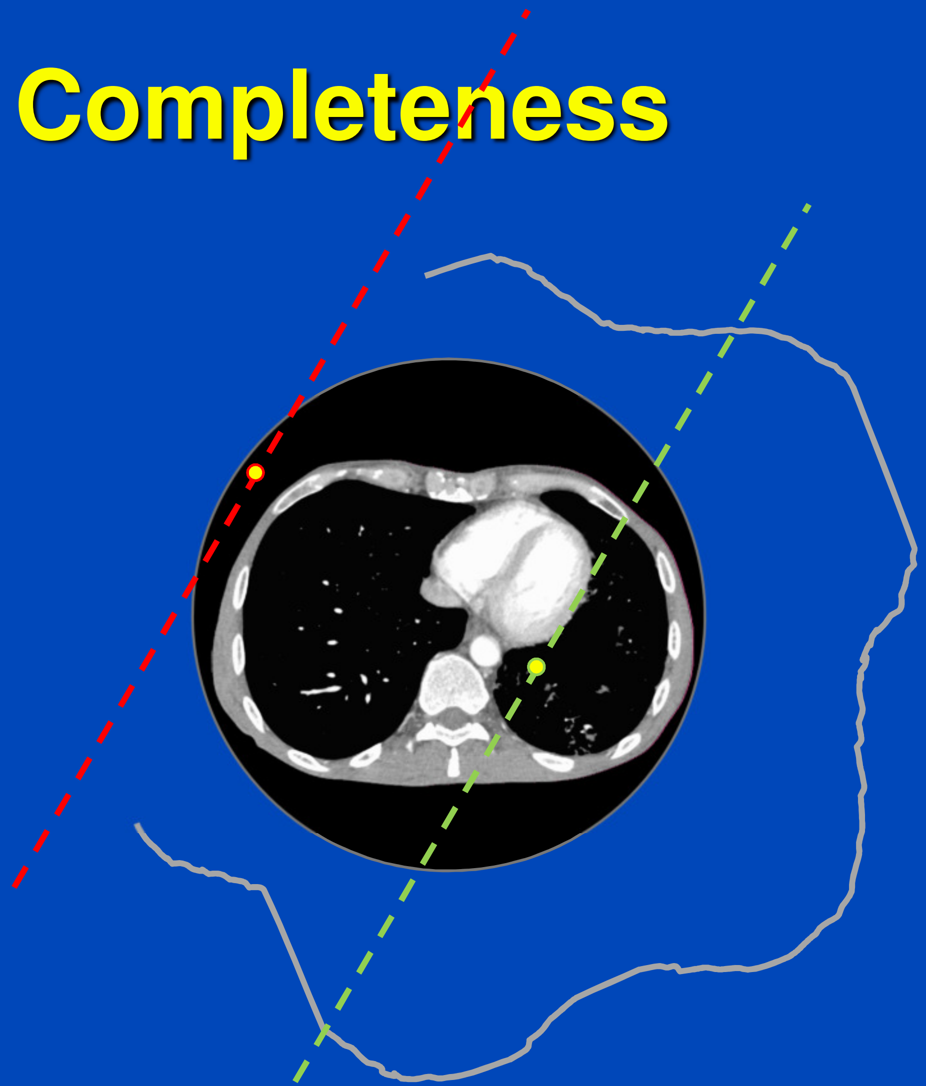
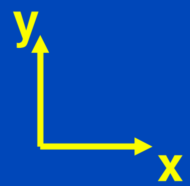
Data Completeness





Any straight line through a voxel must be intersected by the source trajectory at least once.



Emission vs. Transmission

Emission tomography

- Infinitely many sources
- No source trajectory
- Detector trajectory may be an issue
- 3D reconstruction relatively simple

Transmission tomography

- A single source
- Source trajectory is the major issue
- Detector trajectory is an important issue
- 3D reconstruction extremely difficult

Analytical Image Reconstruction

$$x^2 = y$$

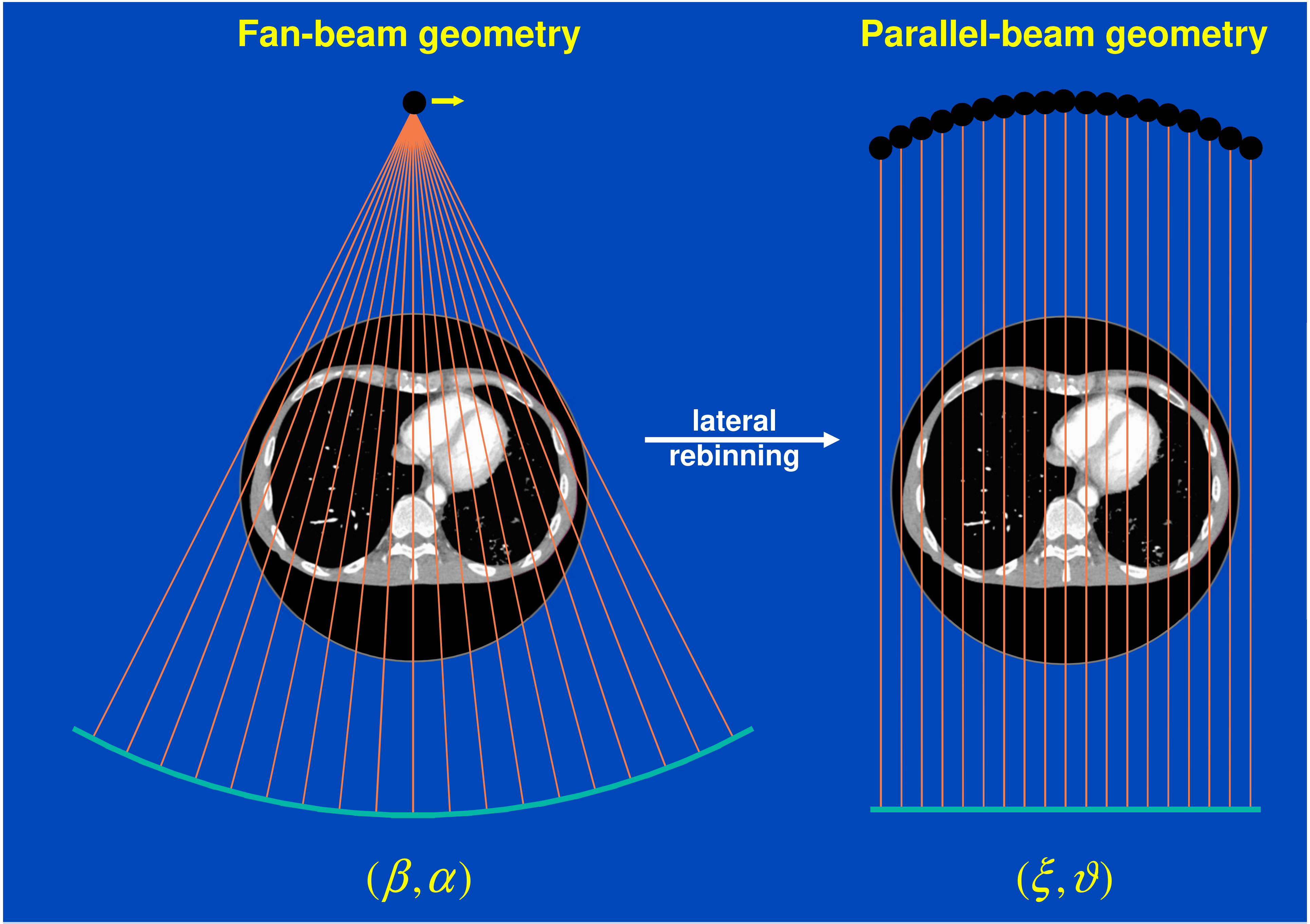
Model

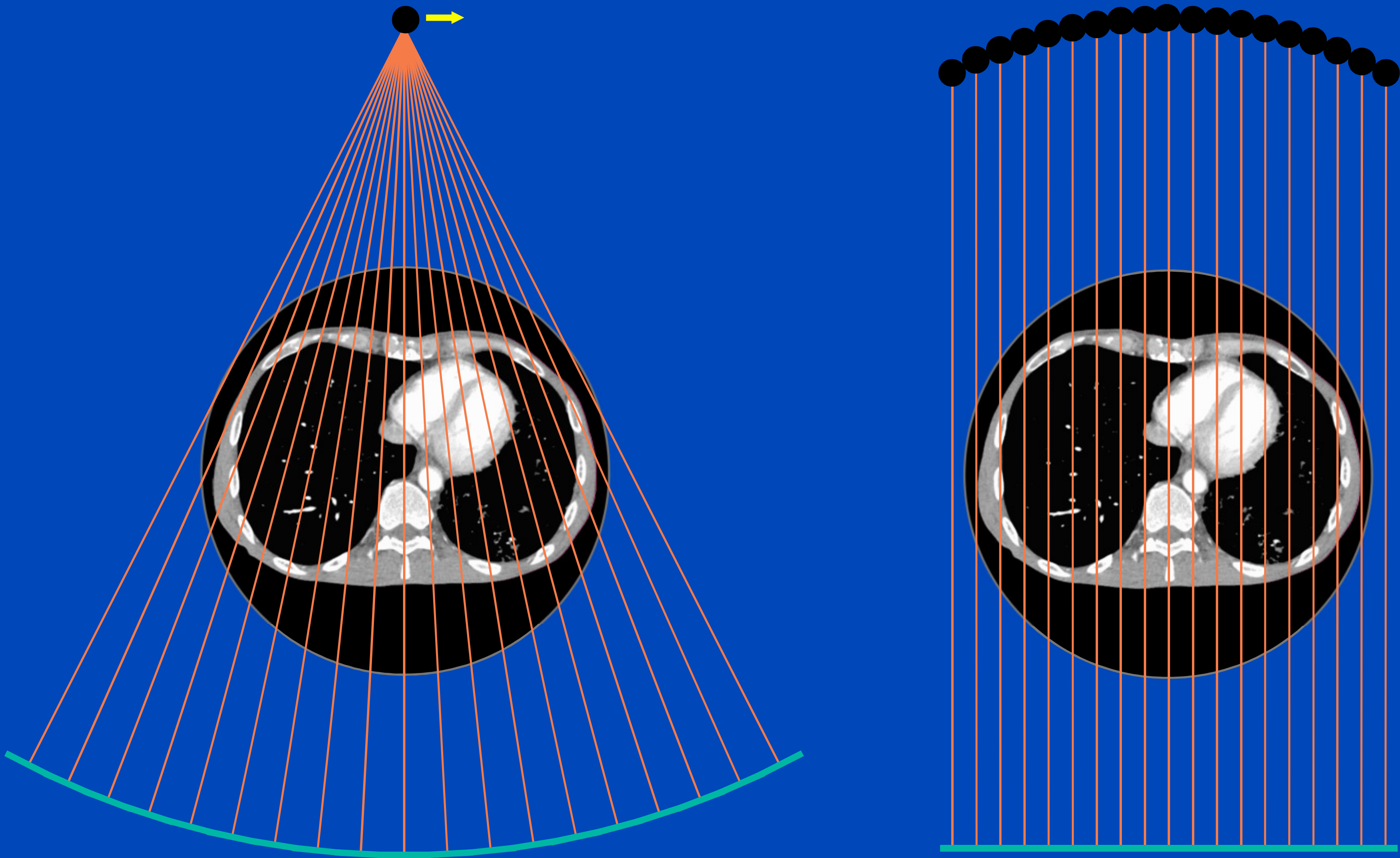
$$x = \sqrt{y}$$

Solution

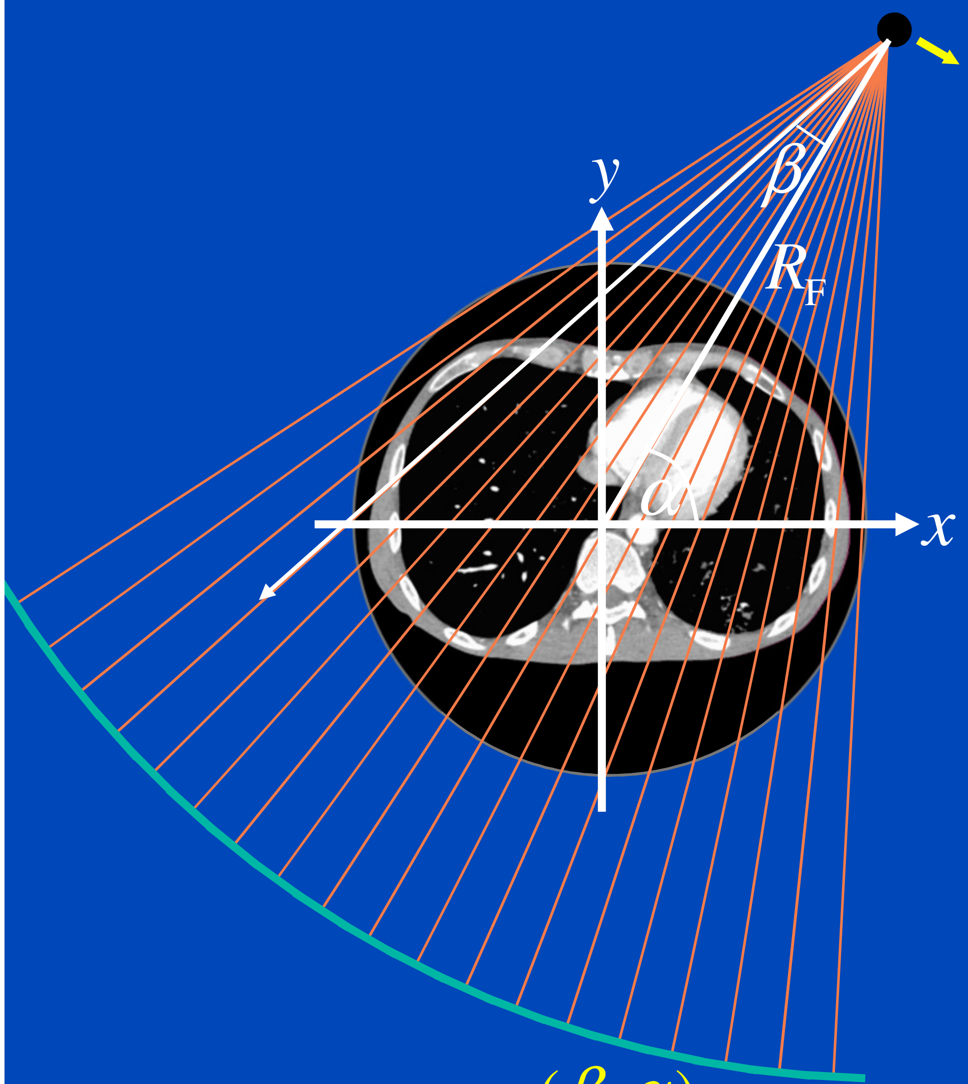
2D: In-Plane Geometry

- Decouples from longitudinal geometry
- Useful for many imaging tasks
- Easy to understand
- 2D reconstruction
  - Rebinning = resampling, resorting
  - Filtered backprojection


Fan-beam geometry
Parallel-beam geometry
lateral
rebinning
(β,α)
(ξ,ϑ)

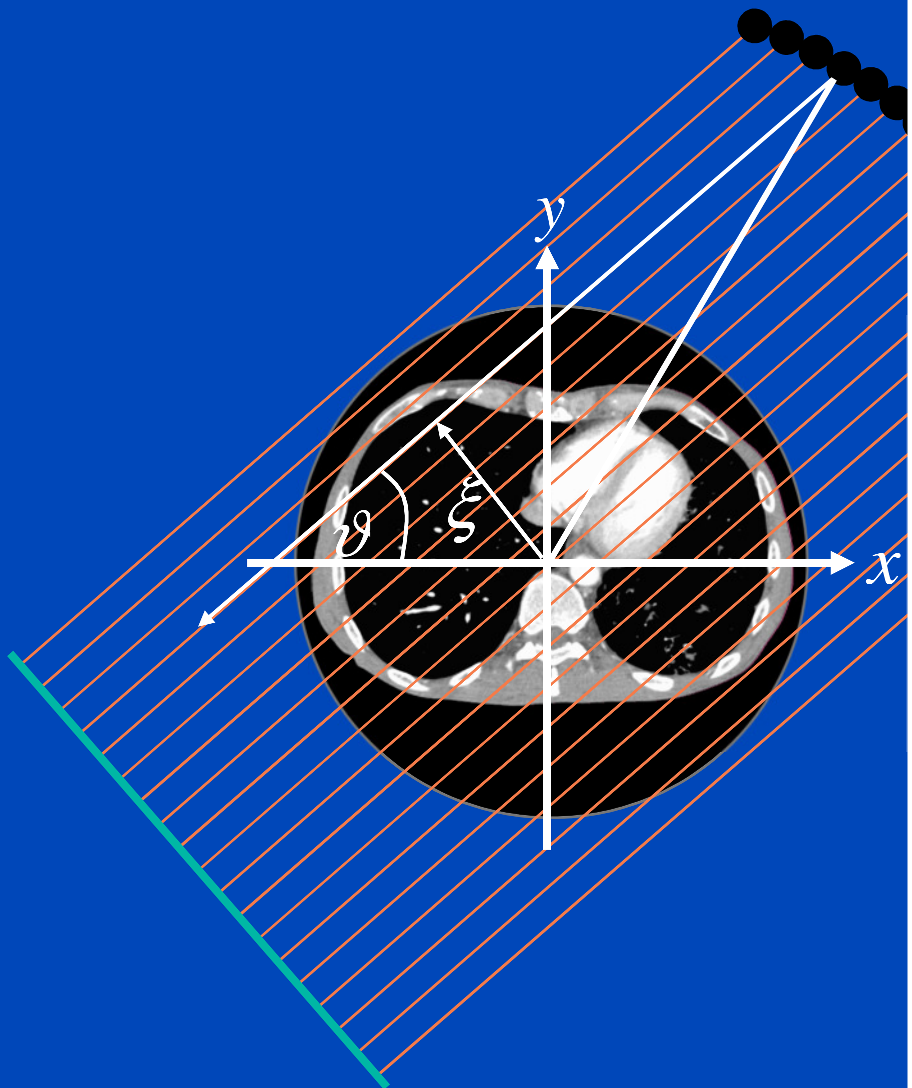


Fan-beam geometry



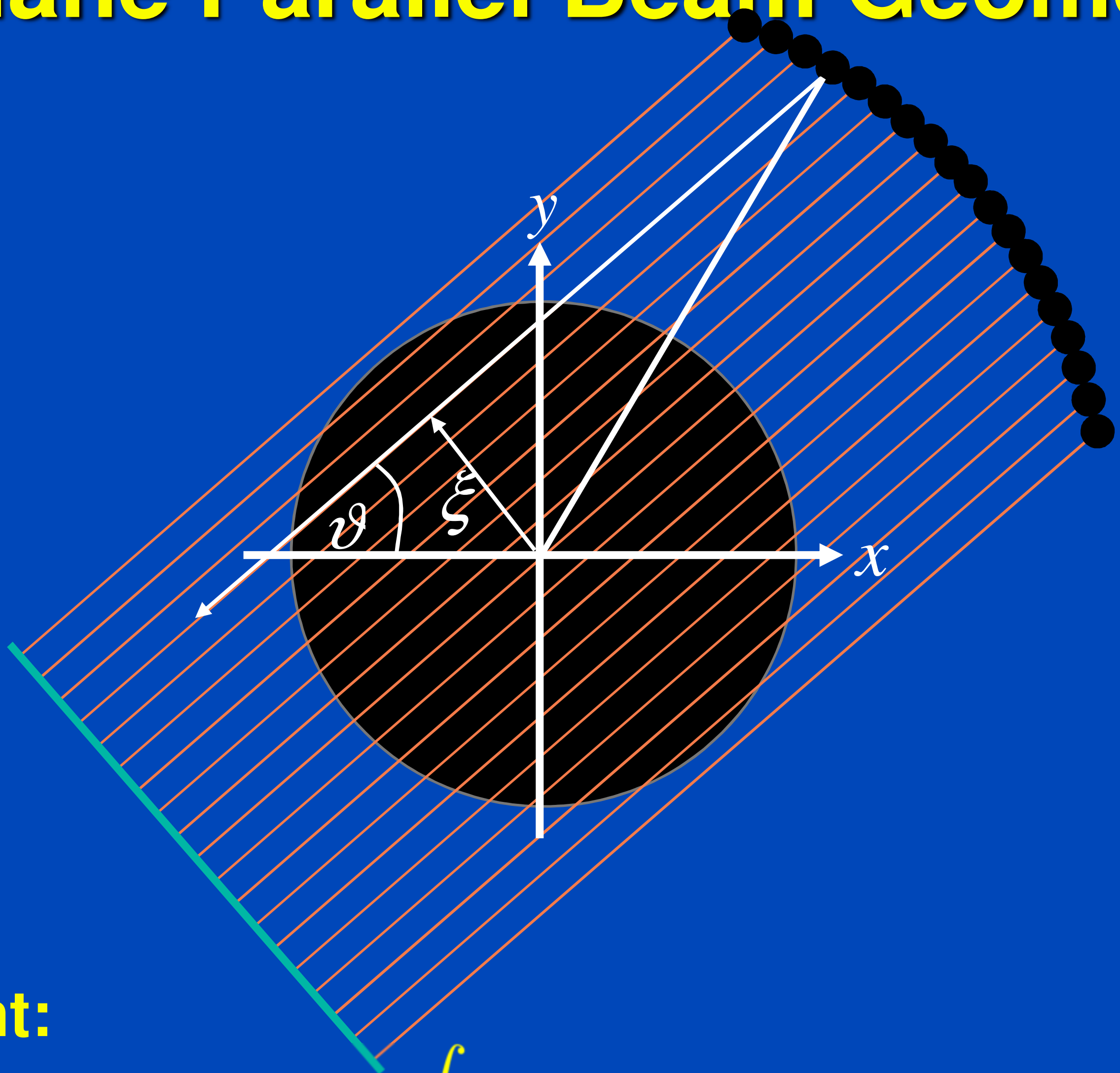
(β,α)

Parallel-beam geometry



(ξ,ϑ)

In-Plane Parallel Beam Geometry



Measurement:

$$p(\vartheta,\xi) = \mathsf{R}f(\vartheta,\xi) = \int dx dy\, f(x,y)\delta(x\cos\vartheta + y\sin\vartheta - \xi)$$

Filtered Backprojection (FBP)

Measurement: $p(\vartheta,\xi) = \int dx dy\, f(x,y)\delta(x\cos\vartheta + y\sin\vartheta - \xi)$

Fourier transform:

$$\int d\xi\, p(\vartheta,\xi)e^{-2\pi i\xi u} = \int dx dy\, f(x,y)e^{-2\pi i u(x\cos\vartheta + y\sin\vartheta)}$$

This is the central slice theorem: $P(\vartheta,u) = F(u\cos\vartheta, u\sin\vartheta)$

Inversion: $f(x,y) = \int_0^\pi d\vartheta \int_{-\infty}^{\infty} du\, |u| P(\vartheta,u) e^{2\pi i u(x\cos\vartheta + y\sin\vartheta)}$

$$= \int_0^\pi d\vartheta\, p(\vartheta,\xi) * k(\xi)\Big|_{\xi = x\cos\vartheta + y\sin\vartheta}$$

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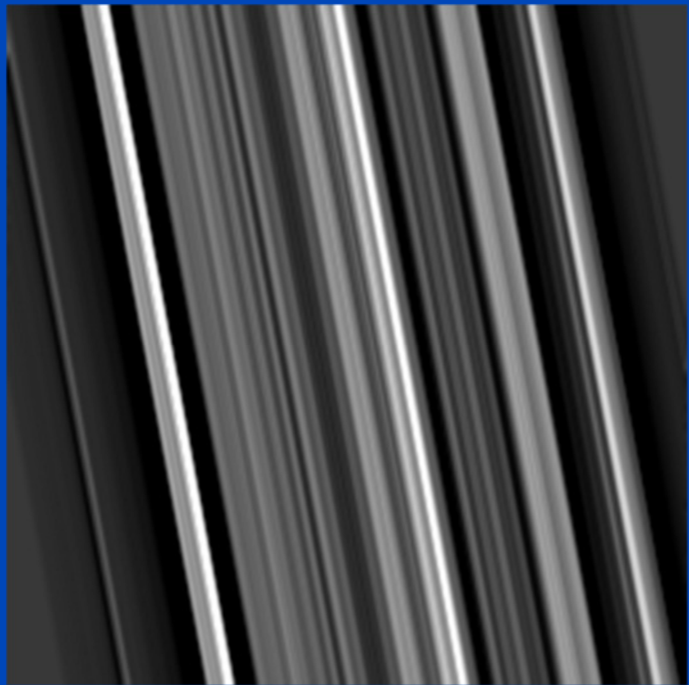
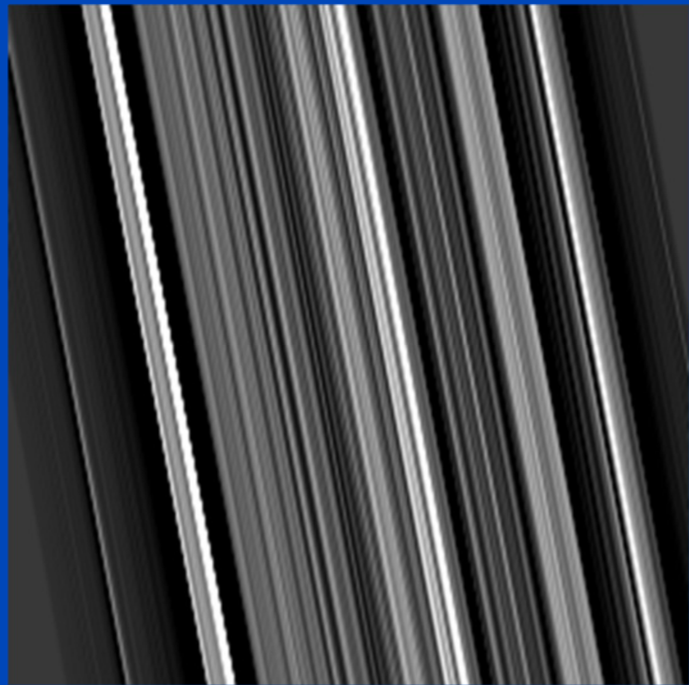
Filtered Backprojection (FBP)

1. Filter projection data with the reconstruction kernel.
2. Backproject the filtered data into the image:

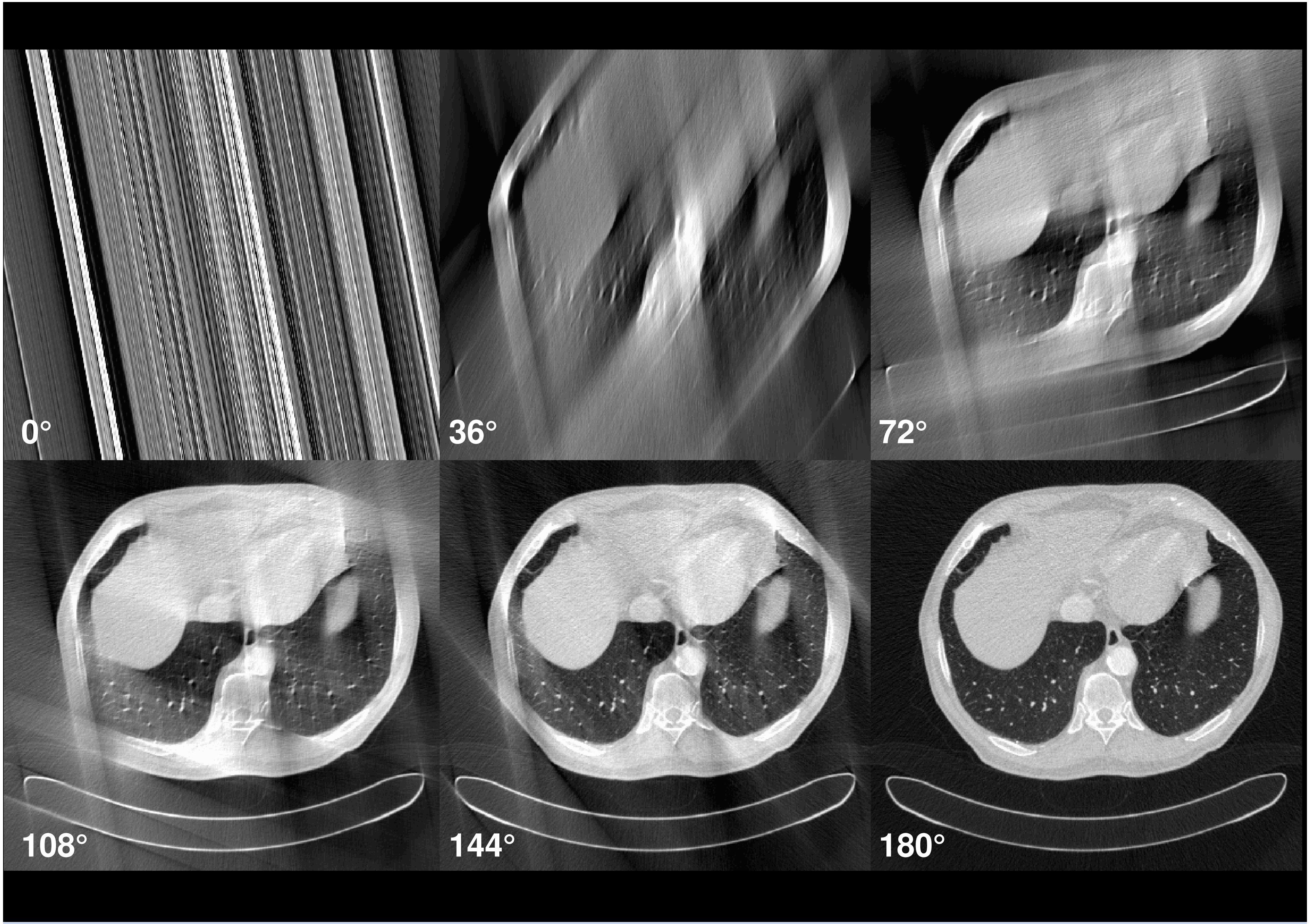


Smooth



Standard

Reconstruction kernels balance between spatial resolution and image noise.



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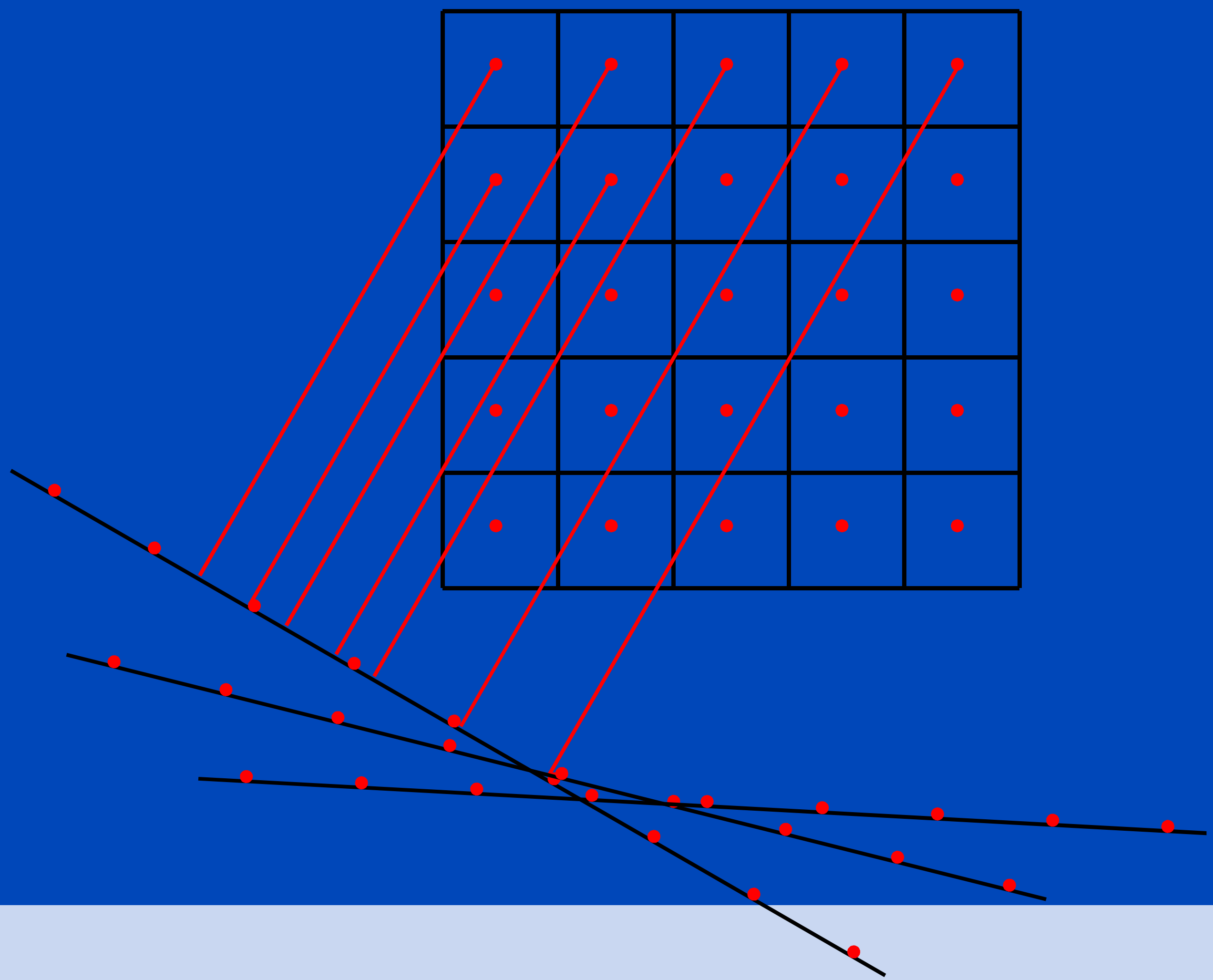
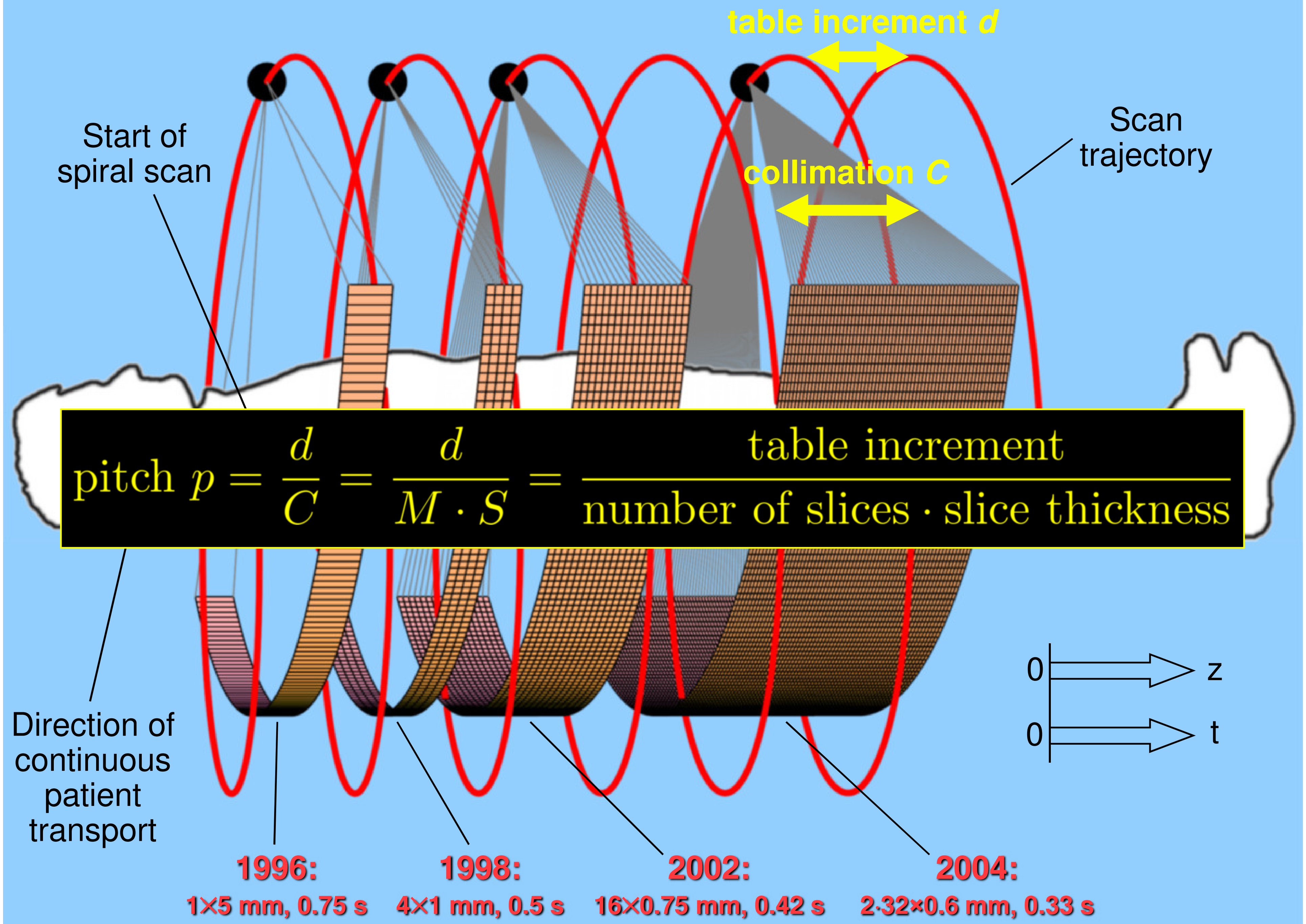
Backprojection

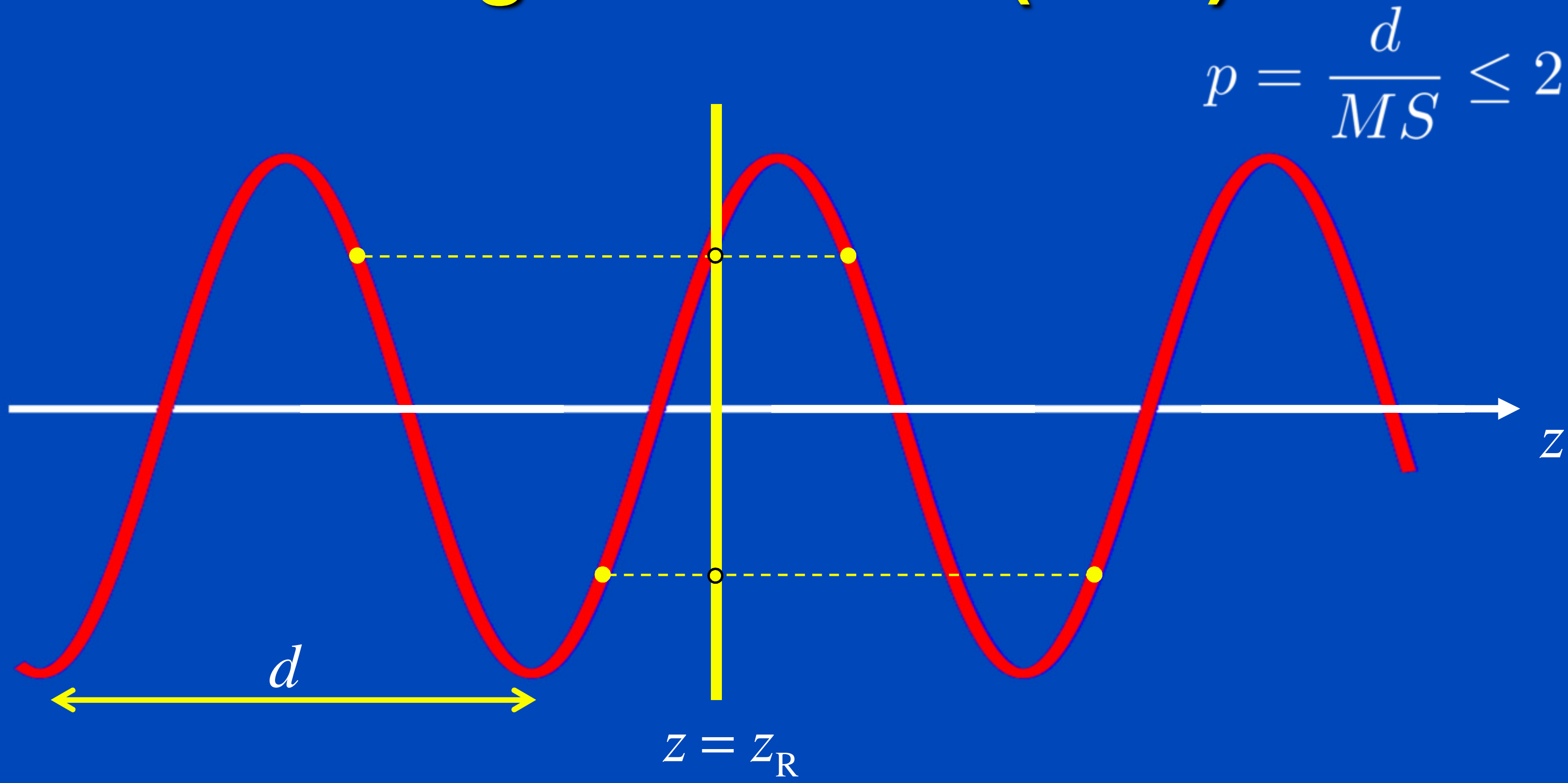




$$\text{pitch } p = \frac{d}{C} = \frac{d}{M \cdot S} = \frac{\text{table increment}}{\text{number of slices} \cdot \text{slice thickness}}$$

Kalender et al., Radiology 173(P):414 (1989) and 176:181-183 (1990)

360° LI Spiral z-Interpolation for Single-Slice CT (*M*=1)



Spiral z-interpolation is typically a linear interpolation between points adjacent to the reconstruction position to obtain circular scan data.

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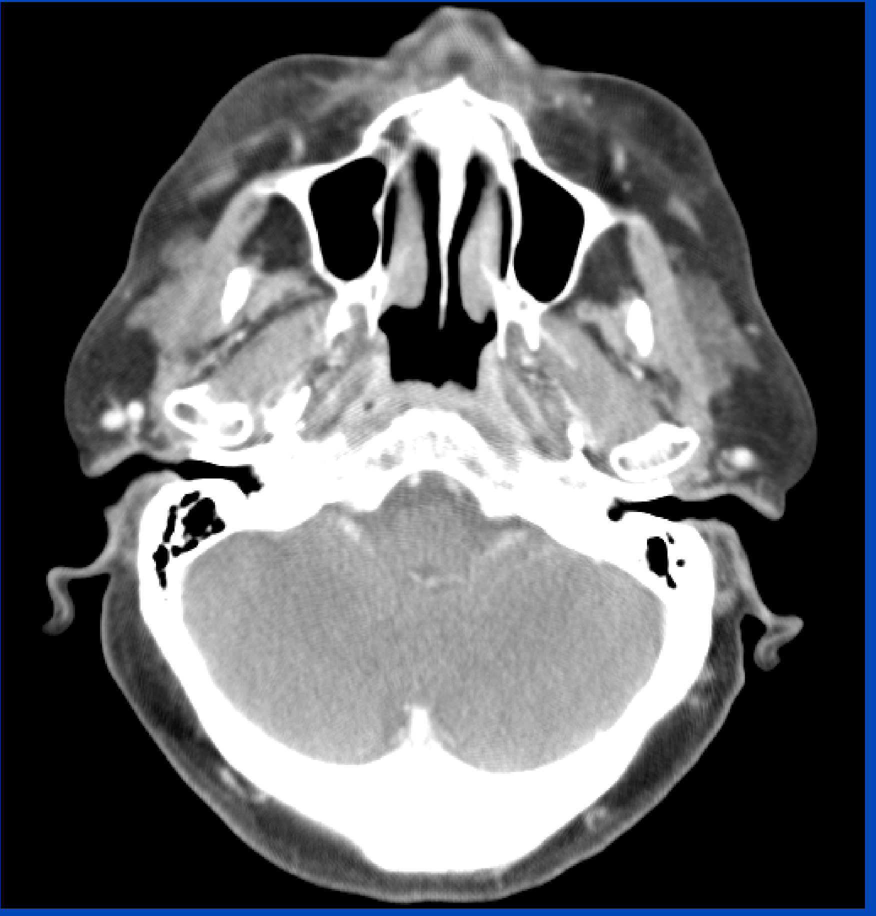
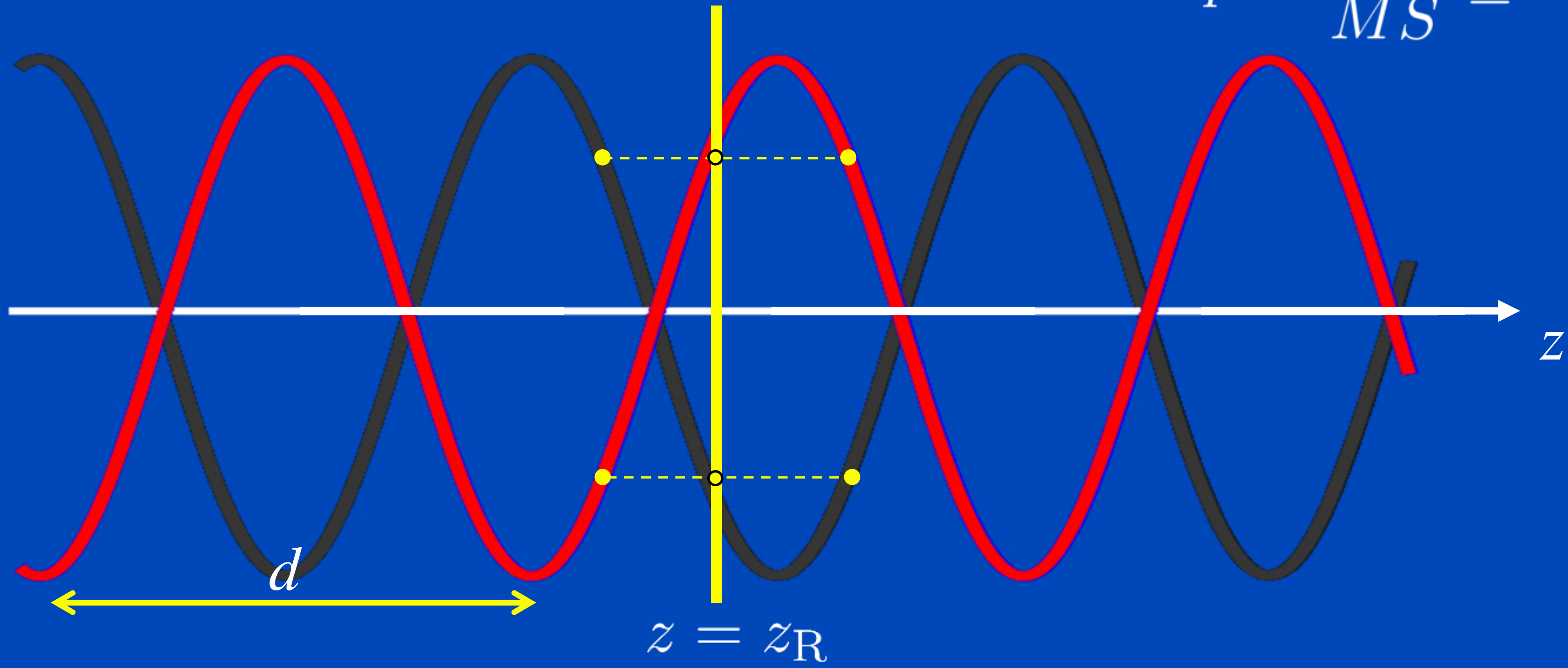
without *z*-interpolation

with *z*-interpolation



180° LI Spiral z-Interpolation for Single-Slice CT (*M*=1)

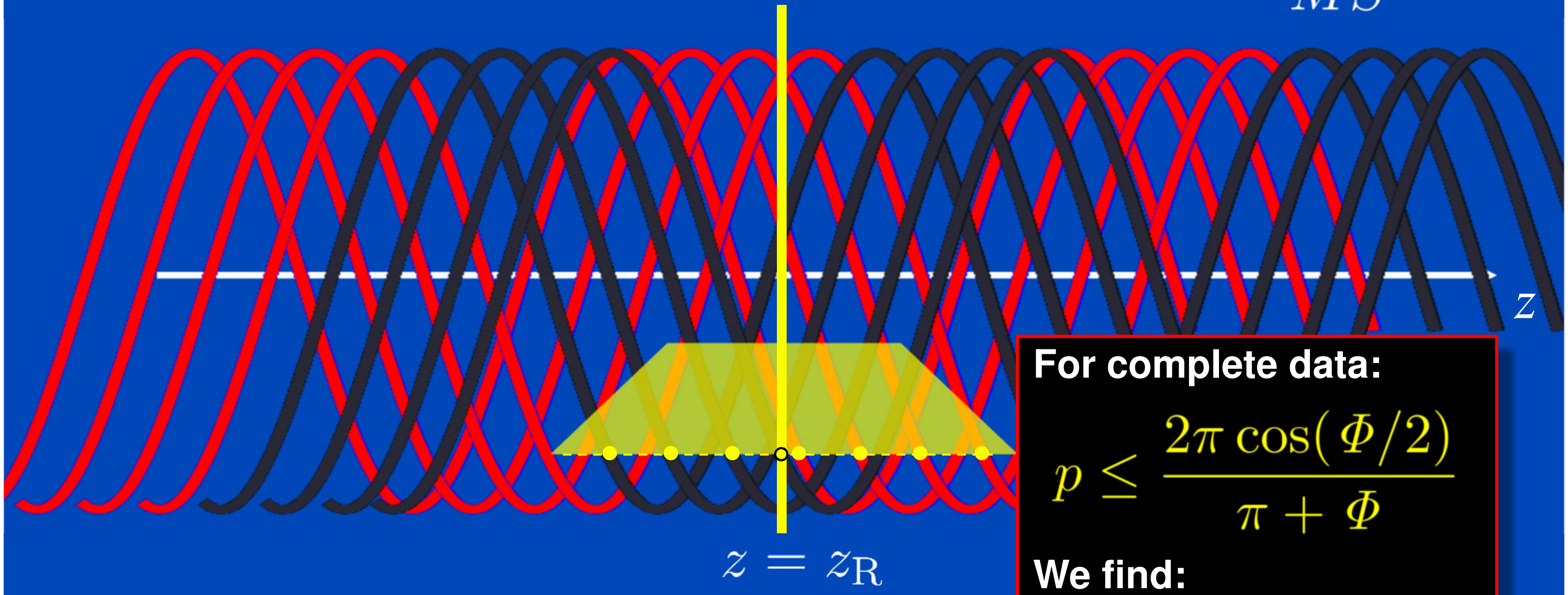
$$p = \frac{d}{MS} \le 2$$



180° spiral z-interpolation interpolates between direct and complementary rays.

Spiral z-Filtering for Multi-Slice CT
M=2, …, 6

$$p = \frac{d}{MS} \leq 1.5$$

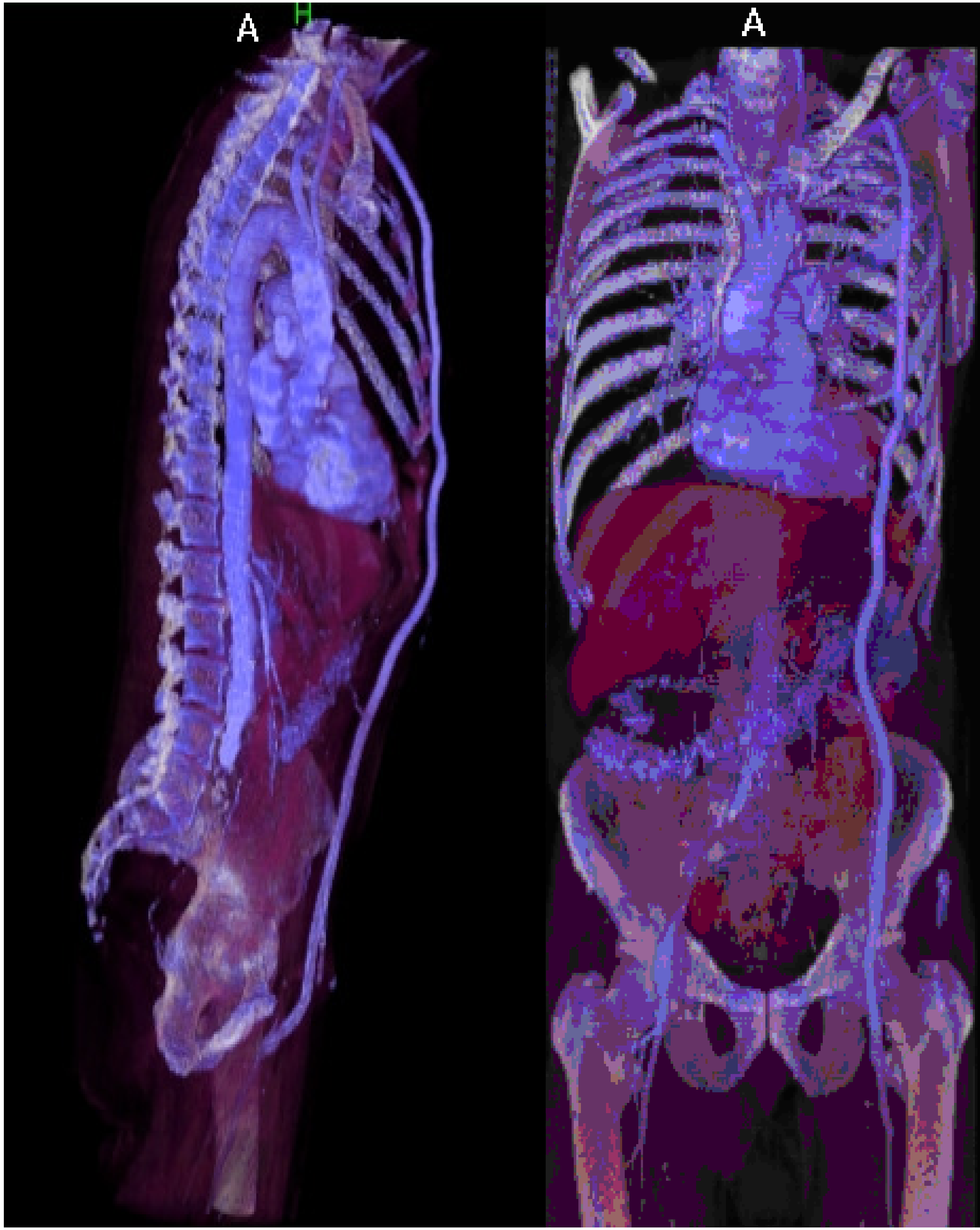


For complete data:

$$p \leq \frac{2\pi \cos(\Phi/2)}{\pi + \Phi}$$

We find:
p ≤ 1.4 for 52° fan angle
p ≤ 1.5 for 43° fan angle

Spiral z-filtering is collecting data points weig… **trapezoidal distance weight to obtain circular scan data.**

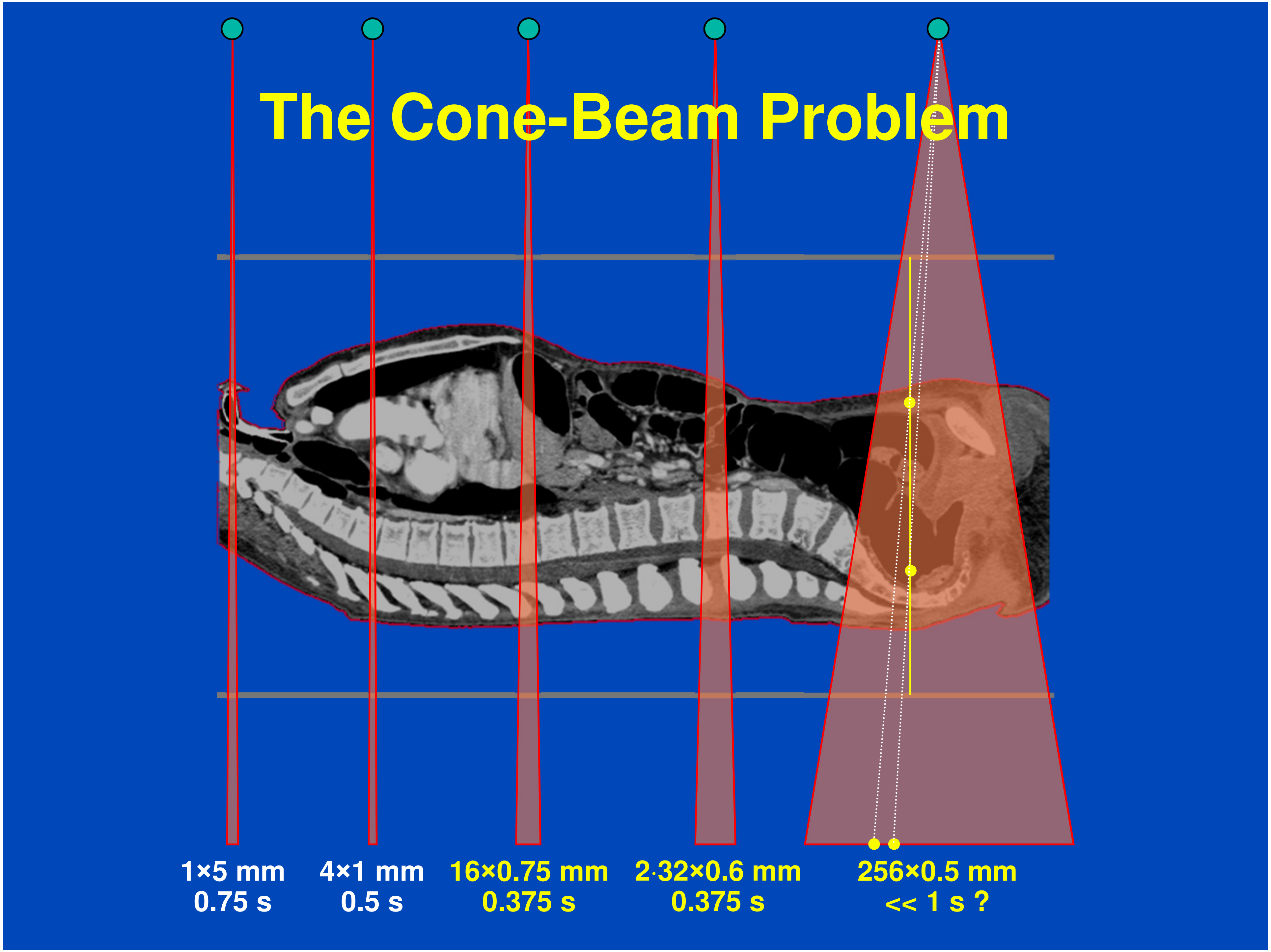


CT Angiography: Axillo-femoral bypass

M = 4

120 cm in 40 s

0.5 s per rotation
4×2.5 mm collimation
pitch 1.5


The Cone-Beam Problem
1×5 mm
0.75 s
4×1 mm
0.5 s
16×0.75 mm
0.375 s
2·32×0.6 mm
0.375 s
256×0.5 mm
<< 1 s ?

Advanced single-slice rebinning in cone-beam spiral CT

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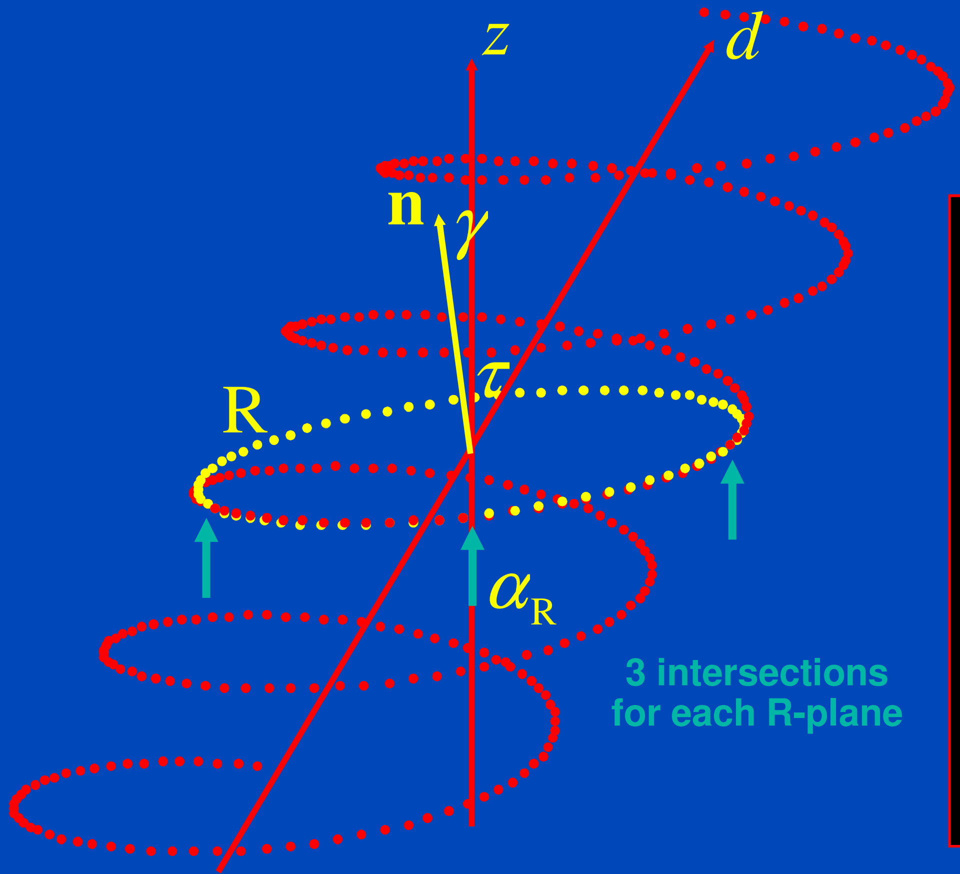
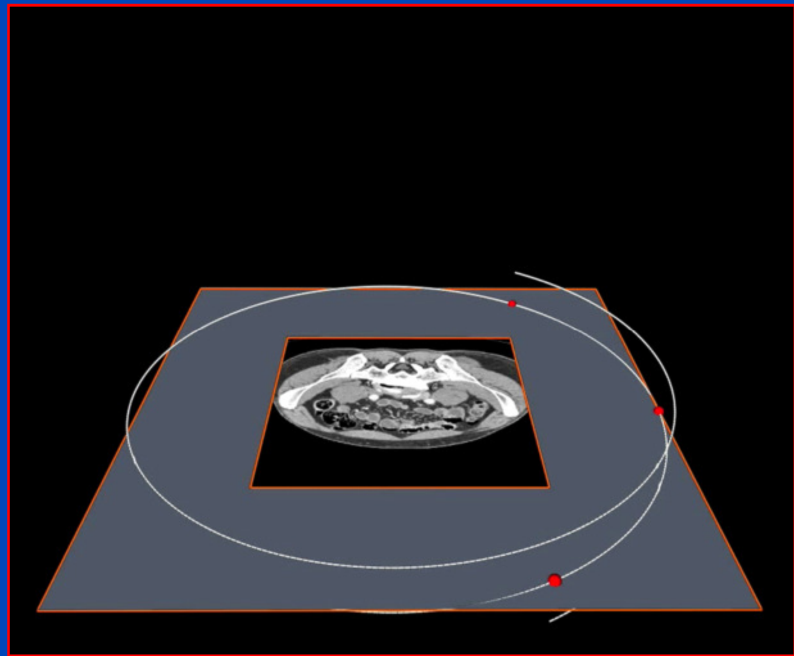
To achieve higher volume coverage at improved z-resolution in computed tomography (CT), systems with a large number of detector rows are demanded. However, handling an increased number of detector rows, as compared to today's four-slice scanners, requires to accounting for the cone geometry of the beams. Many so-called cone-beam reconstruction algorithms have been proposed during the last decade. None met all the requirements of the medical spiral cone-beam CT in regard to the need for high image quality, low patient dose and low reconstruction times. We therefore propose an approximate cone-beam algorithm which uses virtual reconstruction planes tilted to optimally fit 180° spiral segments, i.e., the advanced single-slice rebinning (ASSR) algorithm. Our algorithm is a modification of the single-slice rebinning algorithm proposed by Noo *et al.* [Phys. Med. Biol. **44**, 561–570 (1999)] since we use tilted reconstruction slices instead of transaxial slices to approximate the spiral path. Theoretical considerations as well as the reconstruction of simulated phantom data in comparison to the gold standard 180°LI (single-slice spiral CT) were carried out. Image artifacts, z-resolution as well as noise levels were evaluated for all simulated scanners. Even for a high number of detector rows the artifact level in the reconstructed images remains comparable to that of 180°LI. Multiplanar reformations of the Defrise phantom show none of the typical cone-beam artifacts usually appearing when going to larger cone angles. Image noise as well as the shape of the respective slice sensitivity profiles are equivalent to the single-slice spiral reconstruction, z-resolution is slightly decreased. The ASSR has the potential to become a practical tool for medical spiral cone-beam CT. Its computational complexity lies in the order of standard single-slice CT and it allows to use available 2D backprojection hardware. [S0094-2405(00)00804-X]

Key words: computed tomography (CT), spiral CT, multi-slice CT, cone-beam detector systems, 3D reconstruction

The ASSR Algorithm



$$p = \frac{d}{MS} \leq 1.5$$

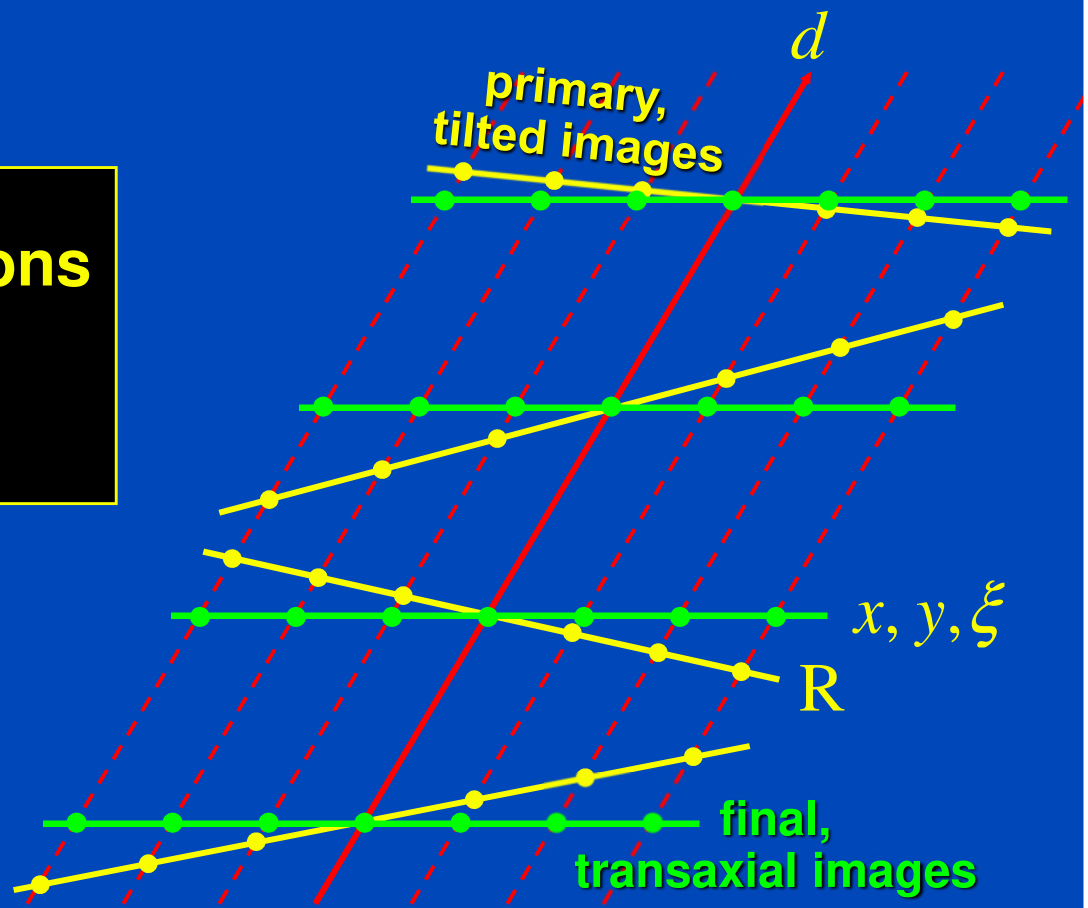


Mean deviation at distance R_M: $\Delta \approx 0.007 \cdot d$

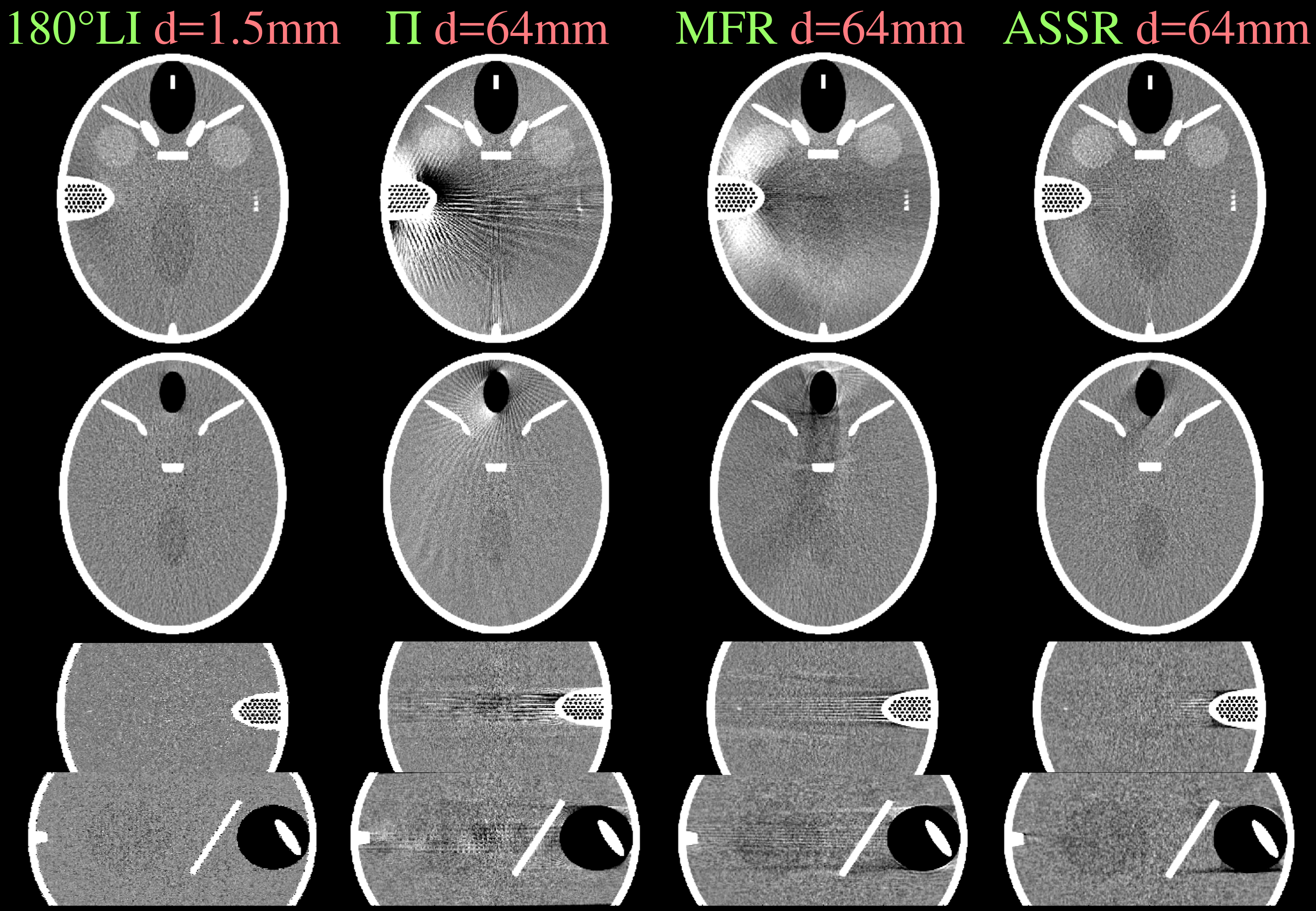
at distance R_F: $\Delta \approx 0.014 \cdot d$

d–Filtering in the Image Domain

- **No in-plane interpolations**
- **Interpolation along *d***
- **Arbitrary *d*-filter width**



Comparison to Other Approximate Algorithms

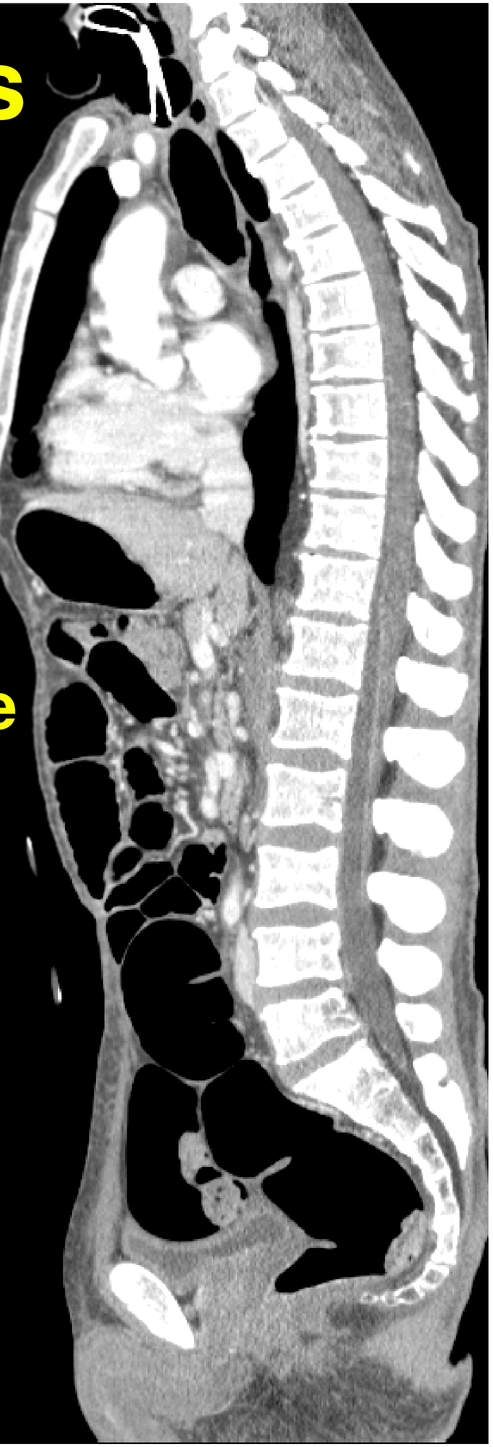


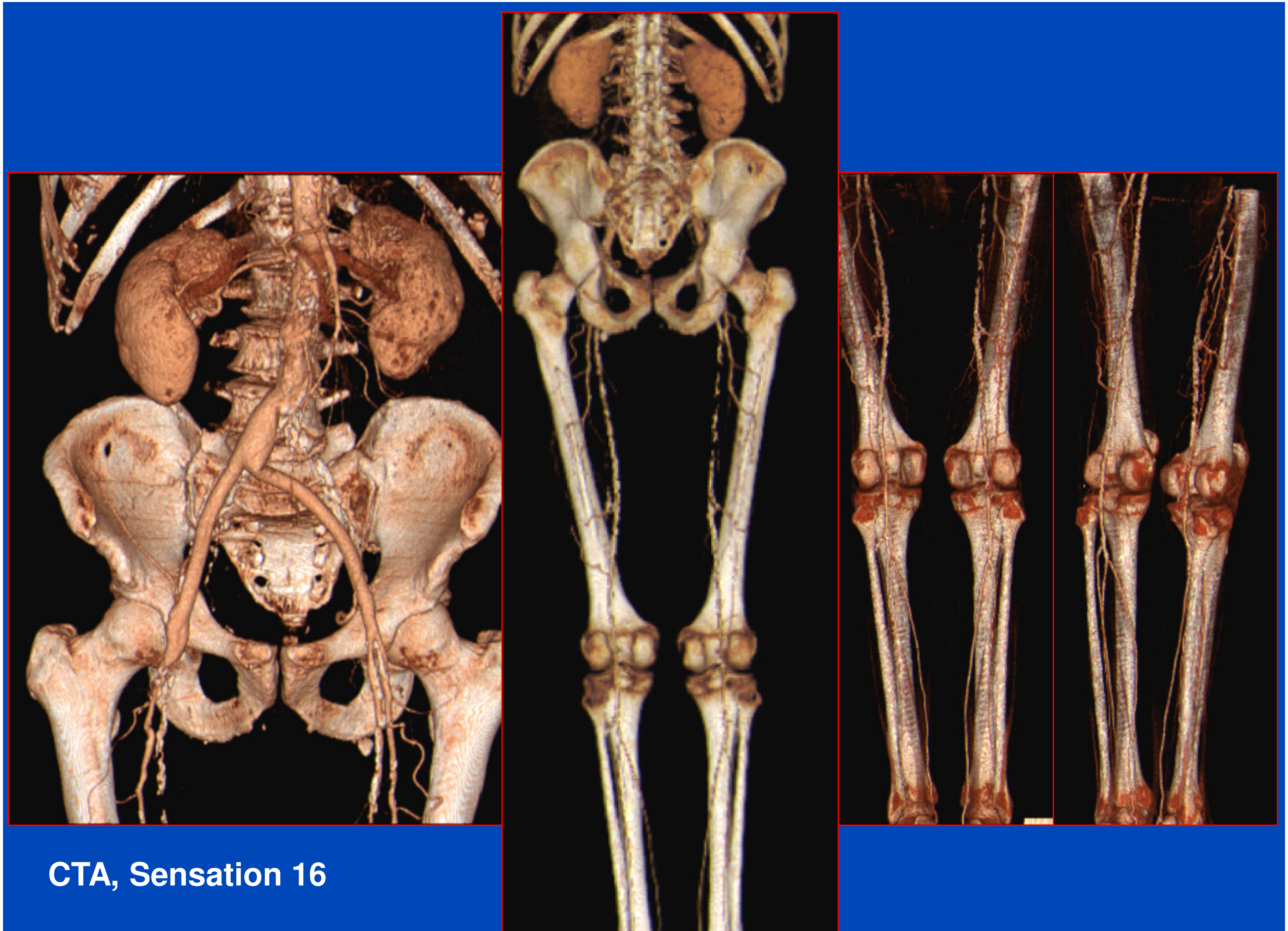
H. Bruder, M. Kachelrieß, S. Schaller. SPIE Med. Imag. Conf. Proc., 3979, 2000

Patient Images with ASSR

- High image quality
- High performance
- Use of available 2D reconstruction hardware
- 100% detector usage
- Arbitrary pitch

- Sensation 16
- 0.5 s rotation
- 16×0.75 mm collimation
- pitch 1.0
- 70 cm in 29 s
- 1.4 GB rawdata
- 1400 images

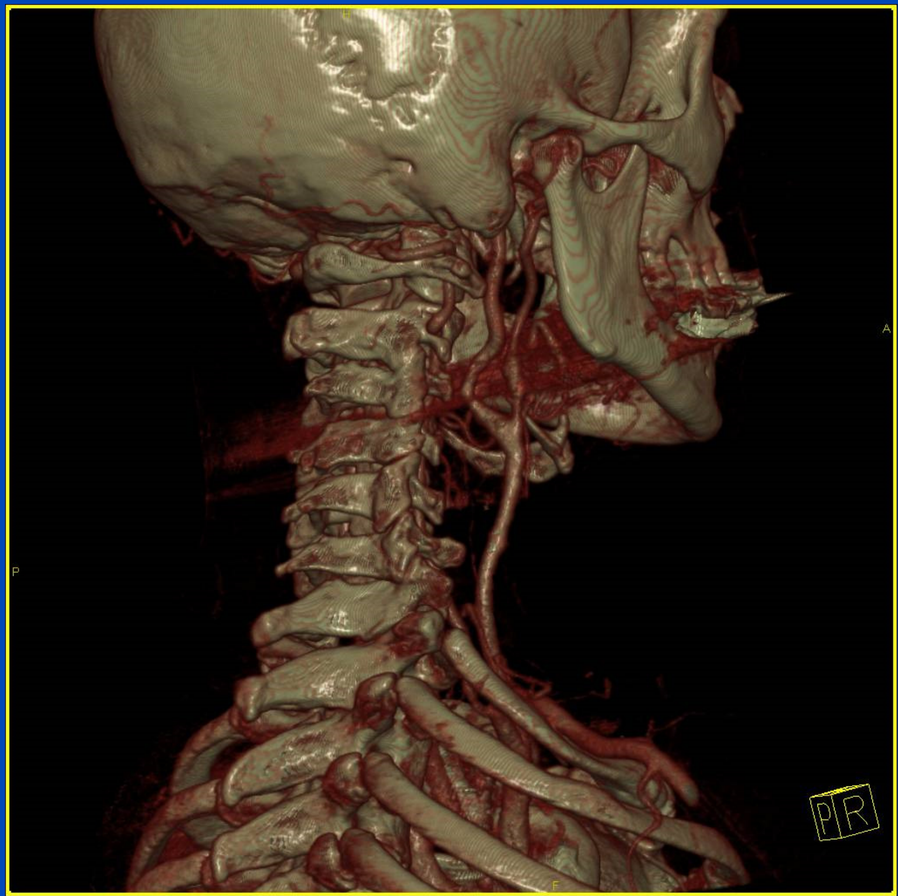


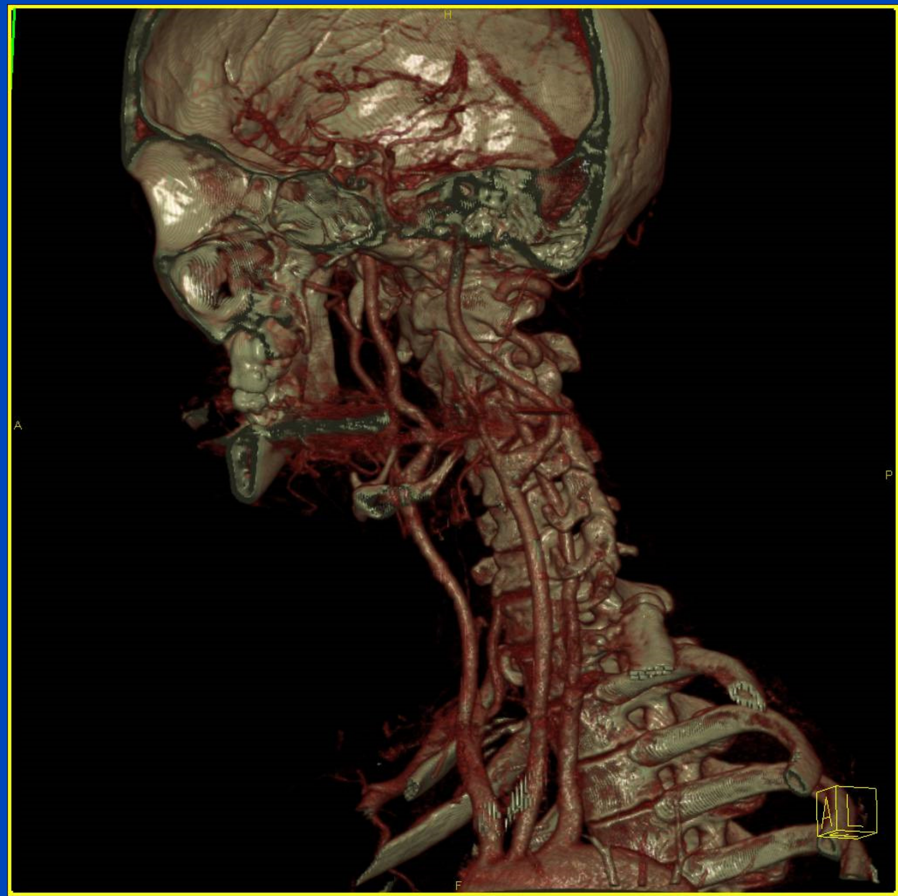


CTA, Sensation 16

Data courtesy of Dr. Michael Lell, Erlangen, Germany

CT-Angiography
Sensation 64 spiral scan with 2·32×0.6 mm and 0.375 s

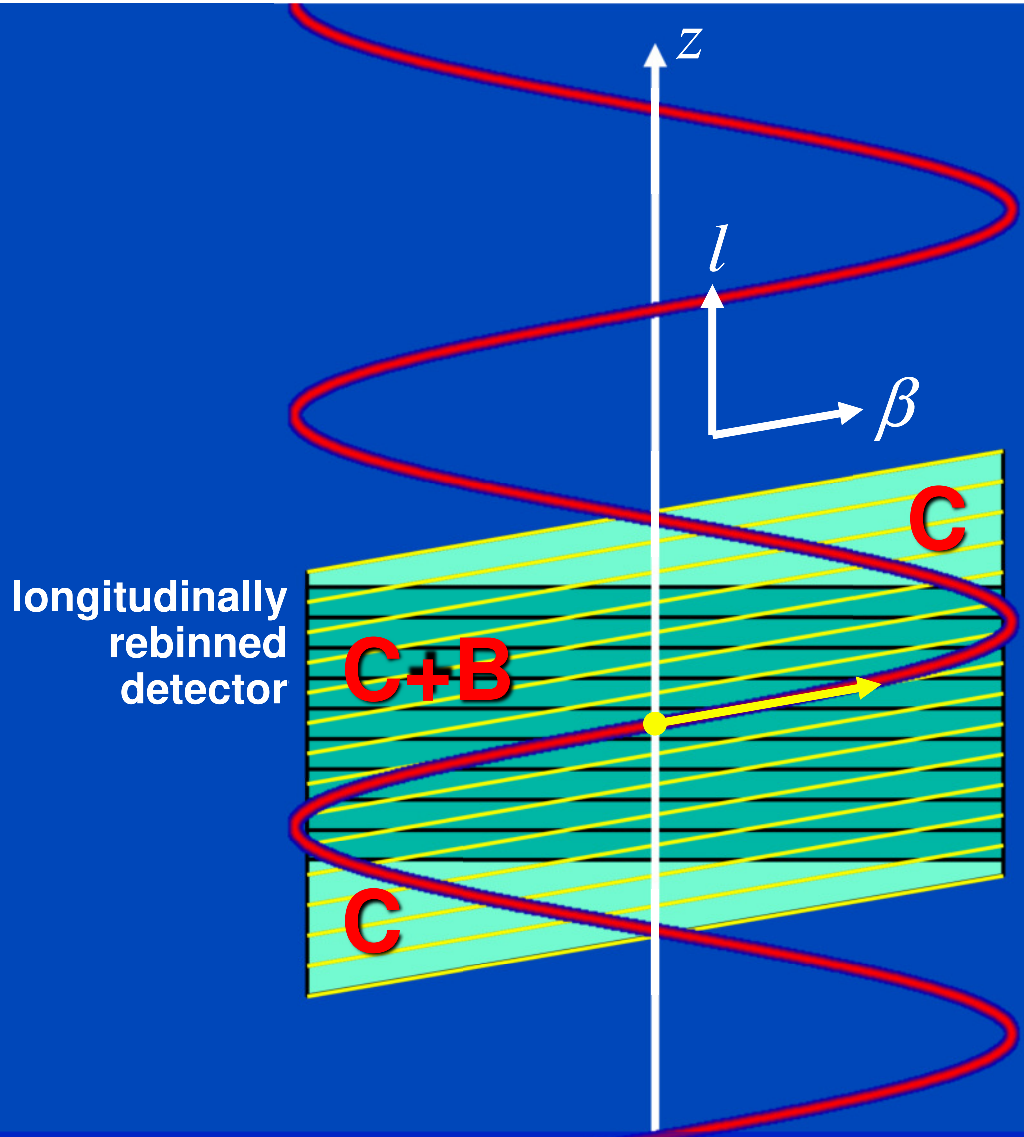




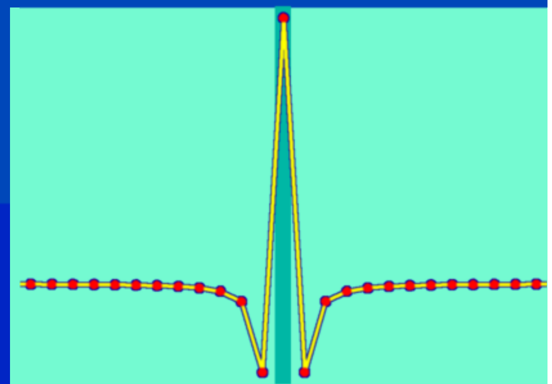
Extended Parallel Backprojection (EPBP)

3D and 4D Feldkamp-Type Image Reconstruction for Large Cone Angles

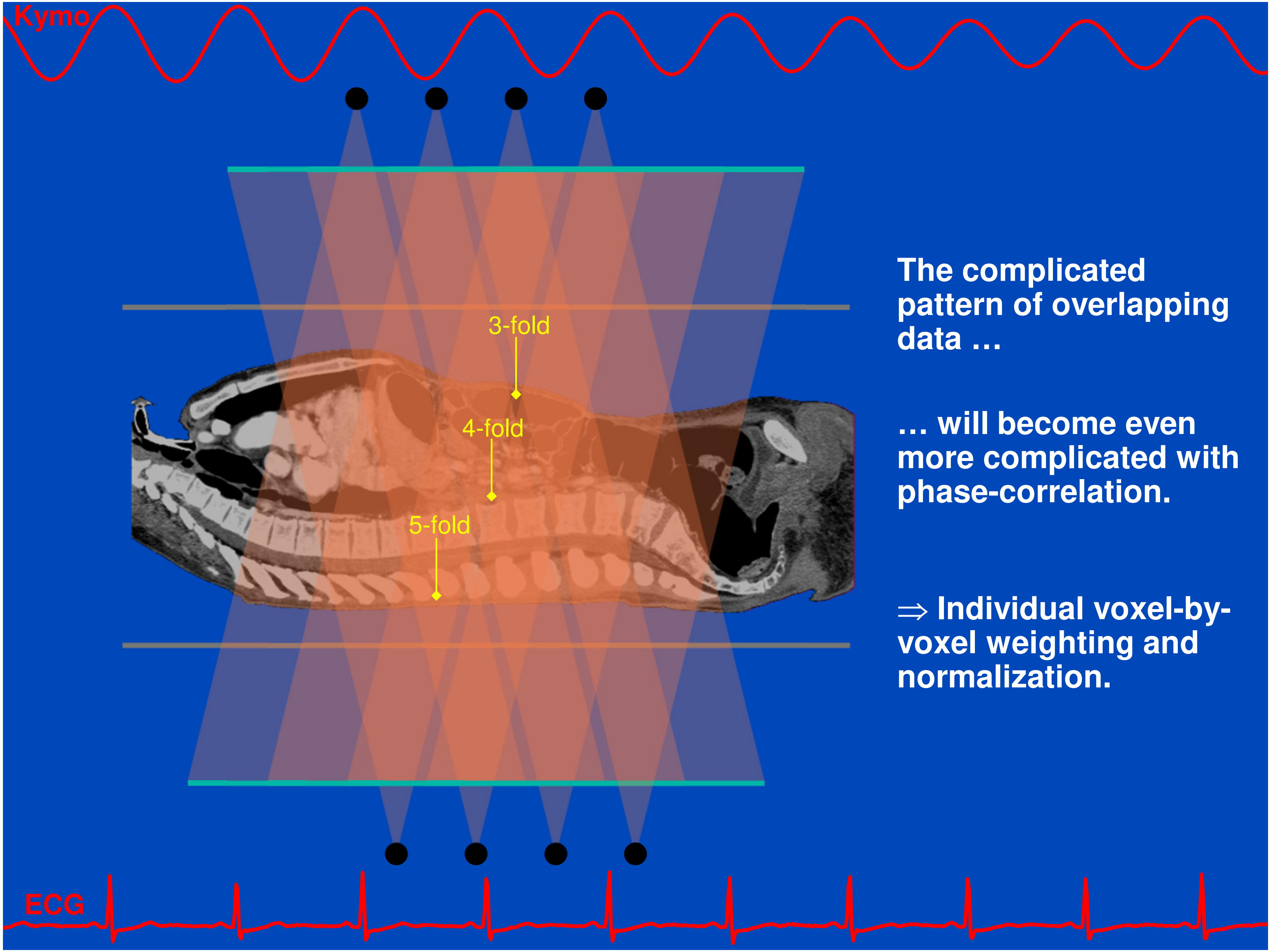
- Trajectories: circle, sequence, spiral
- Scan modes: standard, phase-correlated
- Rebinning: azimuthal + longitudinal + radial
- Feldkamp-type: convolution + true 3D backprojection
- 100% detector usage
- Fast and efficient



$$p = \frac{d}{MS} \leq 1.5$$



C: Area used for convolution
B: Area used for backprojection



The complicated pattern of overlapping data …

… will become even more complicated with phase-correlation.

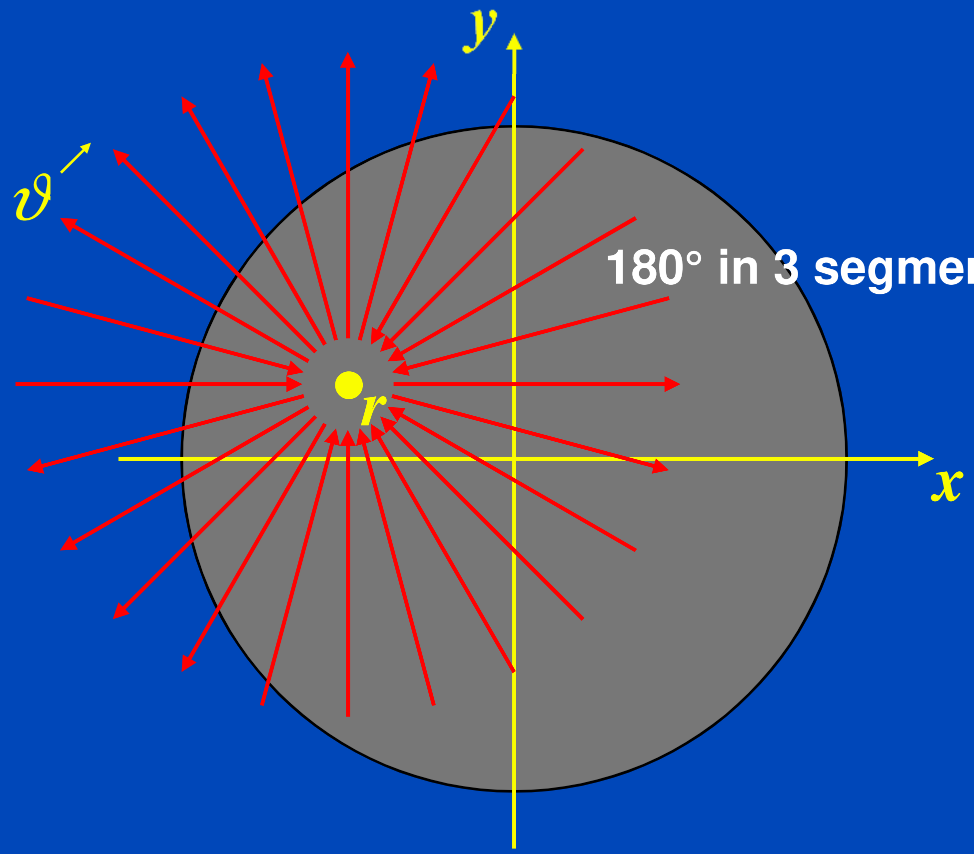
⇒ Individual voxel-by-voxel weighting and normalization.

The 180° Condition

$$\int d\vartheta\, w(\vartheta) = \pi$$

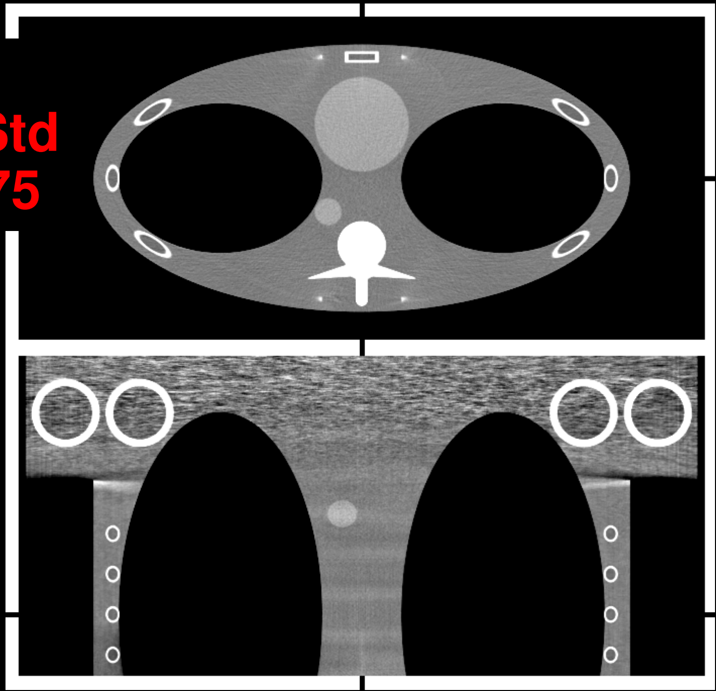
and

$$\sum_k w(\vartheta + k\pi) = 1$$

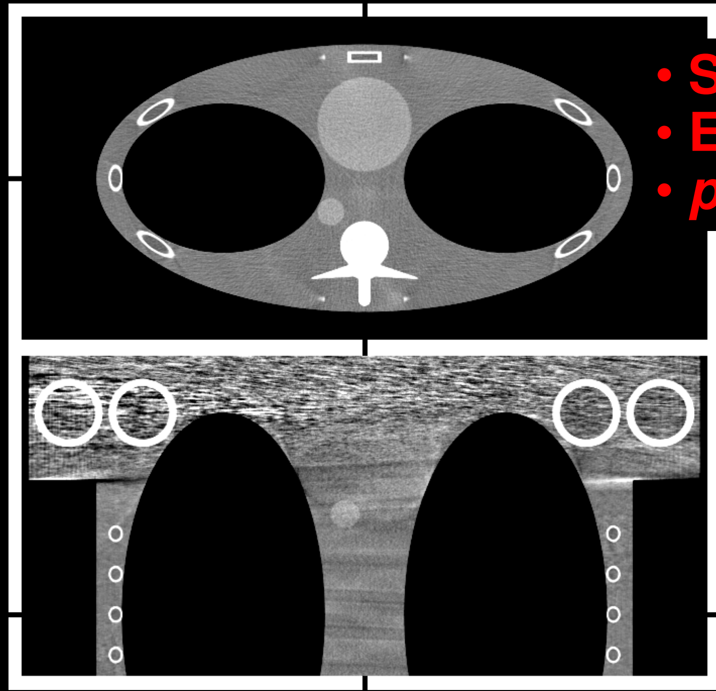


The (weighted) contributions to each object point must make up an interval of 180° and weight 1.

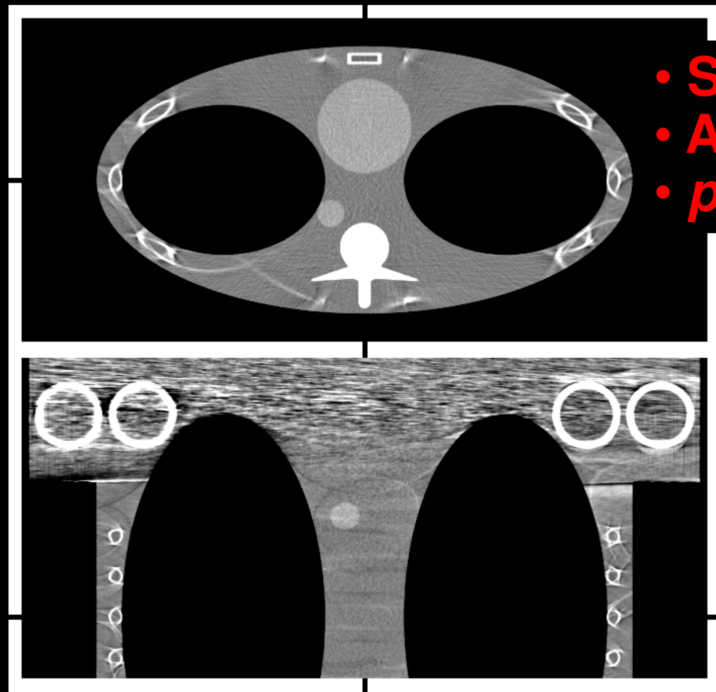
- Spiral
- EPBP Std
- p = 0.375



- Spiral
- EPBP Std
- p = 1.0

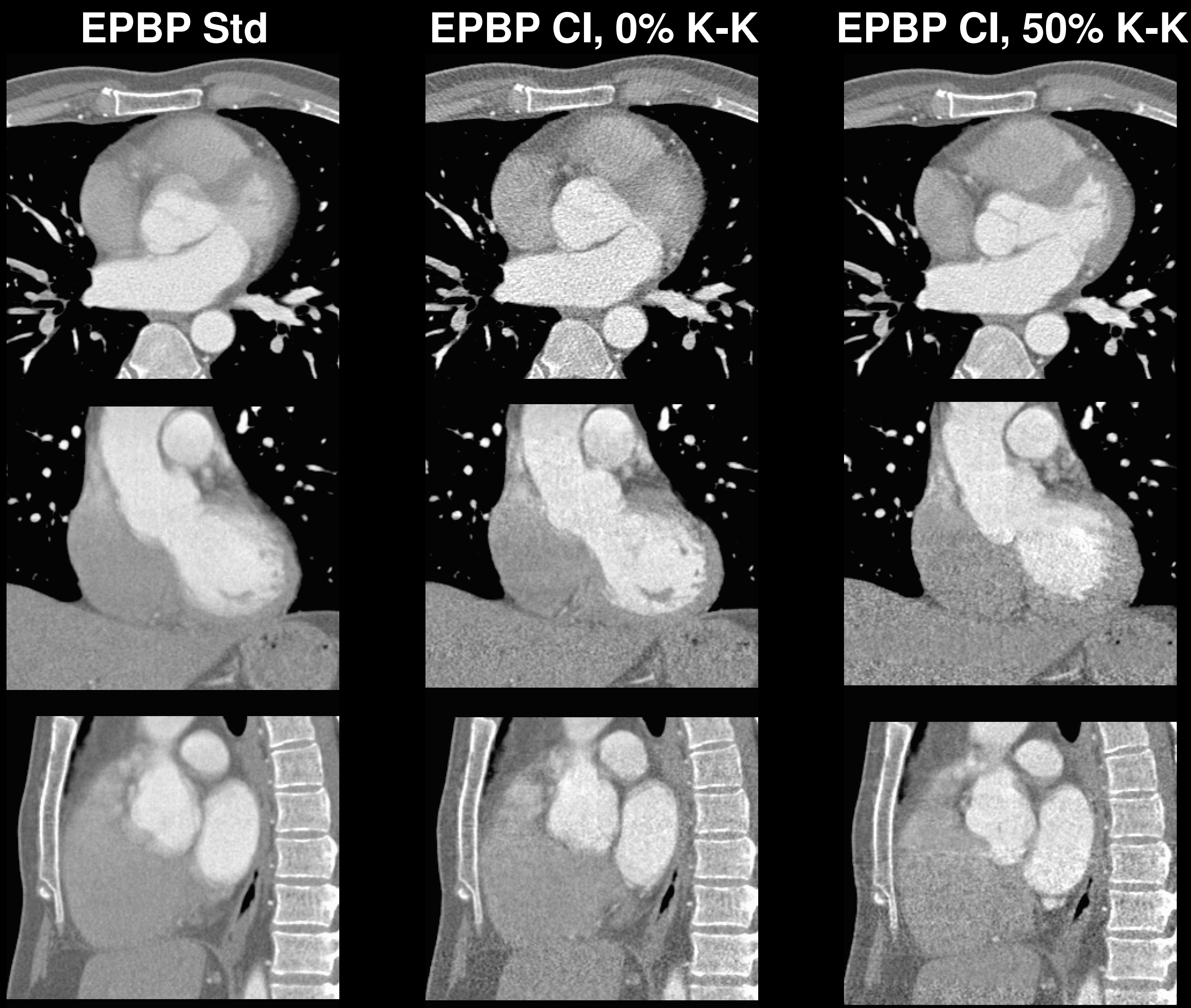


- Spiral
- ASSR Std
- p = 1.0



- 256 slices
- (0/300)

Kachelrieß et al., RSNA 2002, Fully3D 2003 and Med. Phys. 31(6): 1623-1641, 2004



Patient example, 32x0.6 mm, z-FFS, p=0.23, t_{rot}=0.375 s.

Iterative Image Reconstruction

$$x^2 = y$$

Model

$$x = \sqrt{y}$$ (crossed out)

$$(x_n + \Delta x_n)^2 = y$$

$$x_n^2 + 2x_n\Delta x_n + \Delta x_n^2 = y$$ (last term crossed out)

$$x_n^2 + 2x_n\Delta x_n \approx y$$

$$\Delta x_n = \tfrac{1}{2}(y - x_n^2)/x_n$$

$$x_{n+1} = x_n + \Delta x_n$$

Update equation

This is an iterative solution.

dkfz.

Influence of Update Equation and Model

$0.5\,(3-x_n^2)/x_n$	$0.4\,(3-x_n^2)/x_n$	$0.5\,(3-x_n^{2.1})/x_n$
$x_0 = 1.$	$x_0 = 1.$	$x_0 = 1.$
$x_1 = 2.$	$x_1 = 1.8$	$x_1 = 2.$
$x_2 = 1.75$	$x_2 = 1.74667$	$x_2 = 1.67823$
$x_3 = 1.73214$	$x_3 = 1.73502$	$x_3 = 1.68833$
$x_4 = 1.73205$	$x_4 = 1.73265$	$x_4 = 1.68723$
$x_5 = 1.73205$	$x_5 = 1.73217$	$x_5 = 1.68734$
$x_6 = 1.73205$	$x_6 = 1.73207$	$x_6 = 1.68733$
$x_7 = 1.73205$	$x_7 = 1.73206$	$x_7 = 1.68733$
$x_8 = 1.73205$	$x_8 = 1.73205$	$x_8 = 1.68733$

$$x^2 = 3, \quad x_0 = 1, \quad x_{n+1} = x_n + \Delta x_n$$

Analytical Reconstruction

1. Problem

$$p(\vartheta, \xi) = \int dx dy\, f(x, y) \delta(x \cos\vartheta + y \sin\vartheta - \xi)$$

2. Solution

$$f(x, y) = \int_0^\pi d\vartheta\, p(\vartheta, \xi) * k(\xi) \Big|_{\xi = x \cos\vartheta + y \sin\vartheta}$$

3. Discretization

$$\boldsymbol{f} = \boldsymbol{R}^{\mathrm{T}} \cdot \boldsymbol{K} \cdot \boldsymbol{p} = \boldsymbol{R}^{\mathrm{T}} \cdot (\boldsymbol{k} * \boldsymbol{p})$$

Classical Iterative Reconstruction

1. Problem

$$p(\vartheta, \xi) = \int dx dy\, f(x, y) \delta(x \cos\vartheta + y \sin\vartheta - \xi)$$

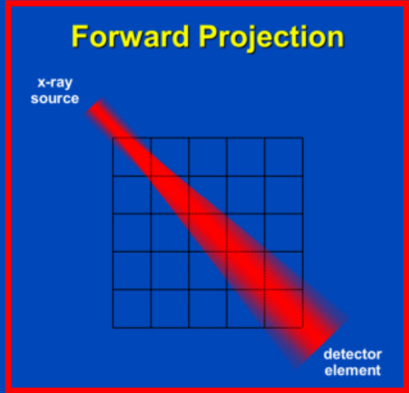
2. Discretization

$$\boldsymbol{p} = \boldsymbol{R} \cdot \boldsymbol{f}$$

3. Solution

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_{\nu} + \boldsymbol{R}^{\mathrm{T}} \cdot \frac{\boldsymbol{p} - \boldsymbol{R} \cdot \boldsymbol{f}_{\nu}}{\boldsymbol{R}^2 \cdot \boldsymbol{1}}$$

CT System Matrix



$$\underbrace{R}_{\text{Radon or x-ray transform}} \cdot \underbrace{f}_{\text{image to be reconstructed}} = \underbrace{p}_{\text{measured rawdata}}$$

$$\boldsymbol{R} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1M} \\ r_{21} & r_{22} & \cdots & r_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & \cdots & r_{NM} \end{pmatrix}, \quad \boldsymbol{f} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_M \end{pmatrix}, \quad \boldsymbol{p} = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_N \end{pmatrix}$$

Kaczmarz's Method

$$\underbrace{\boldsymbol{R}}_{N \times M} \cdot \underbrace{\boldsymbol{f}}_{M \times 1} = \underbrace{\boldsymbol{p}}_{N \times 1}$$

$$\boldsymbol{R} = \begin{pmatrix} \boldsymbol{r}_1 \\ \boldsymbol{r}_2 \\ \vdots \\ \boldsymbol{r}_N \end{pmatrix}, \quad |\boldsymbol{r}_n| = 1$$

$$\boldsymbol{r}_n \cdot \boldsymbol{f} = p_n$$

Kaczmarz's Method (2)

- Successively solve $\boldsymbol{r}_n \cdot \boldsymbol{f} = p_n$
- To do so, project onto the hyperplanes

$$\boldsymbol{r}_n \cdot \left(\boldsymbol{f} + \lambda \boldsymbol{r}_n\right) = p_n$$

$$\lambda = p_n - \boldsymbol{r}_n \cdot \boldsymbol{f}$$

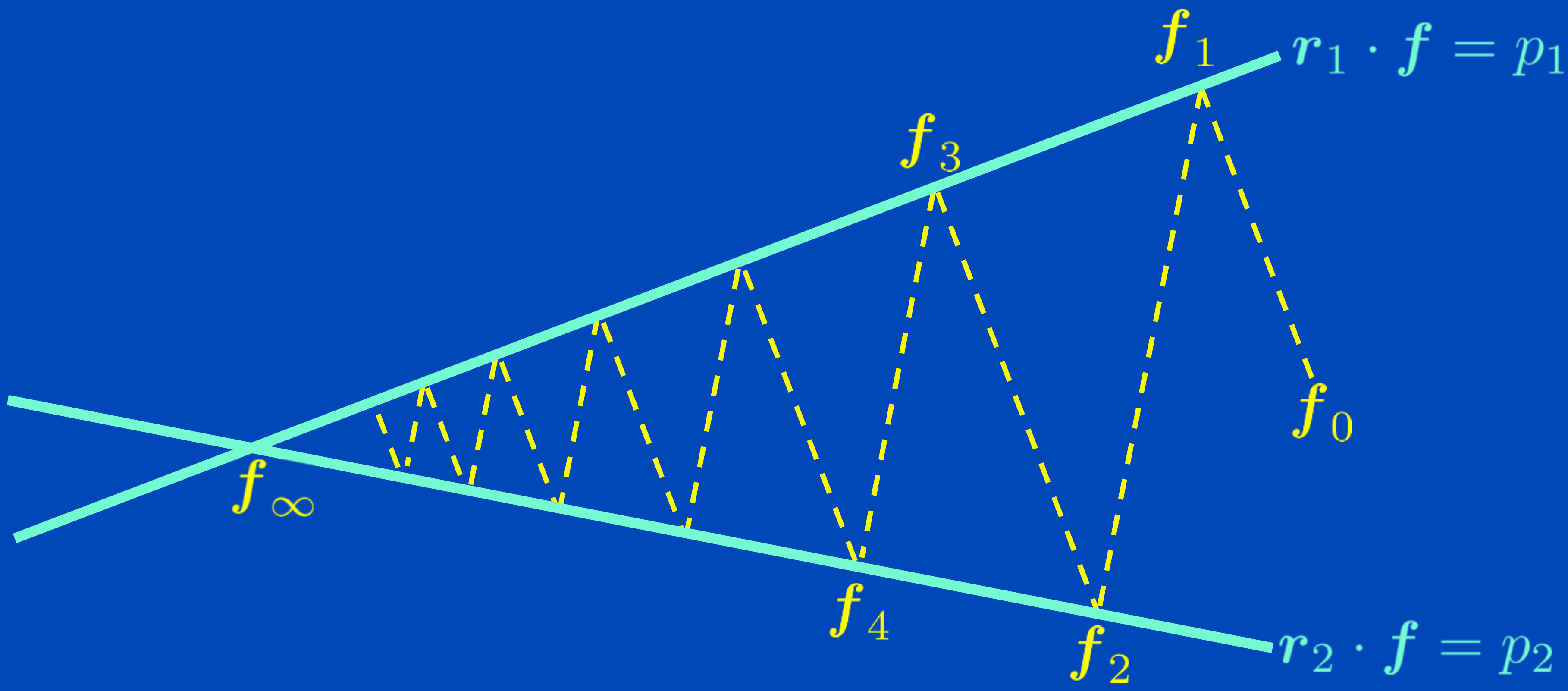
$$\boldsymbol{f}_{\text{new}} = \boldsymbol{f} + \lambda \boldsymbol{r}_n$$

$$\boldsymbol{f}_{\text{new}} = \boldsymbol{f} + \boldsymbol{r}_n \left(p_n - \boldsymbol{r}_n \cdot \boldsymbol{f}\right)$$

- Repeat until some convergence criterion is reached

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{r}_n \left(p_n - \boldsymbol{r}_n \cdot \boldsymbol{f}_\nu\right)$$

Kaczmarz's Method (3)



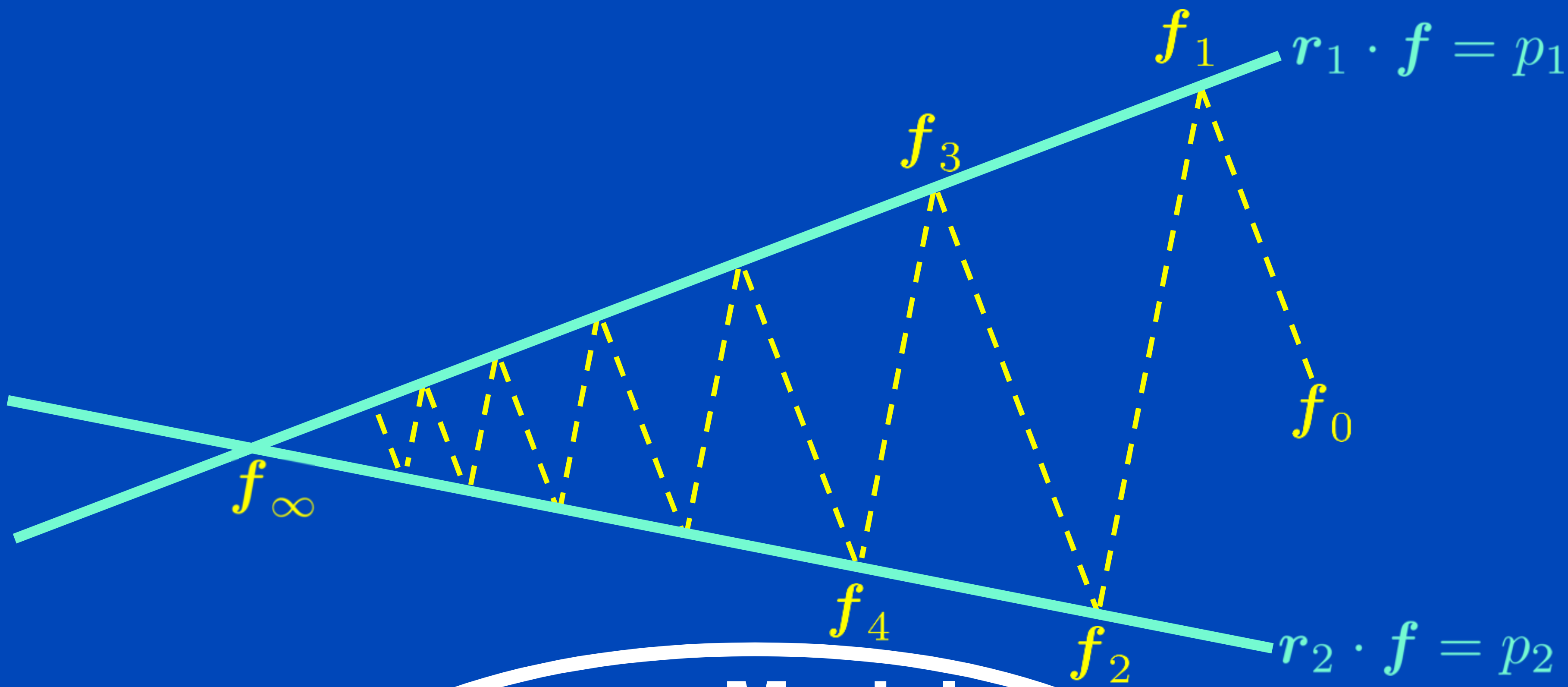
$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{r}_n (p_n - \boldsymbol{r}_n \cdot \boldsymbol{f}_\nu)$$

Kaczmarz in Image Reconstruction: Algebraic Reconstruction Technique (ART)

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{r}_n \big(p_n - \boldsymbol{r}_n \cdot \boldsymbol{f}_\nu \big)$$

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{R}^{\mathrm{T}} \cdot \frac{\boldsymbol{p} - \boldsymbol{R} \cdot \boldsymbol{f}_\nu}{\boldsymbol{R}^2 \cdot \boldsymbol{1}}$$

Kaczmarz‘s Method = ART



Model

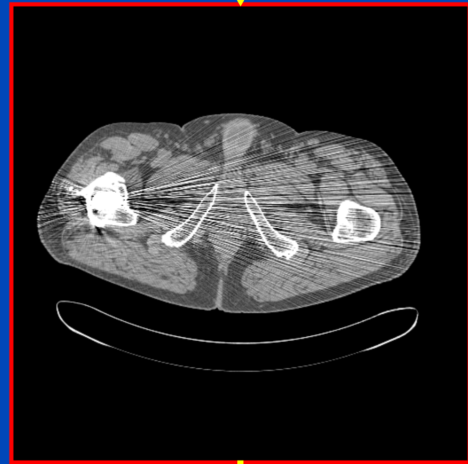
$$f_{\nu+1} = f_\nu + R^{\mathrm{T}} \cdot \frac{p - R \cdot f_\nu}{R^2 \cdot 1}$$

Update equation

Kaczmarz‘s Method = ART

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_{\nu} + \boldsymbol{R}^{\mathrm{T}} \cdot \frac{\boldsymbol{p} - \boldsymbol{R} \cdot \boldsymbol{f}_{\nu}}{\boldsymbol{R}^2 \cdot \mathbf{1}}$$

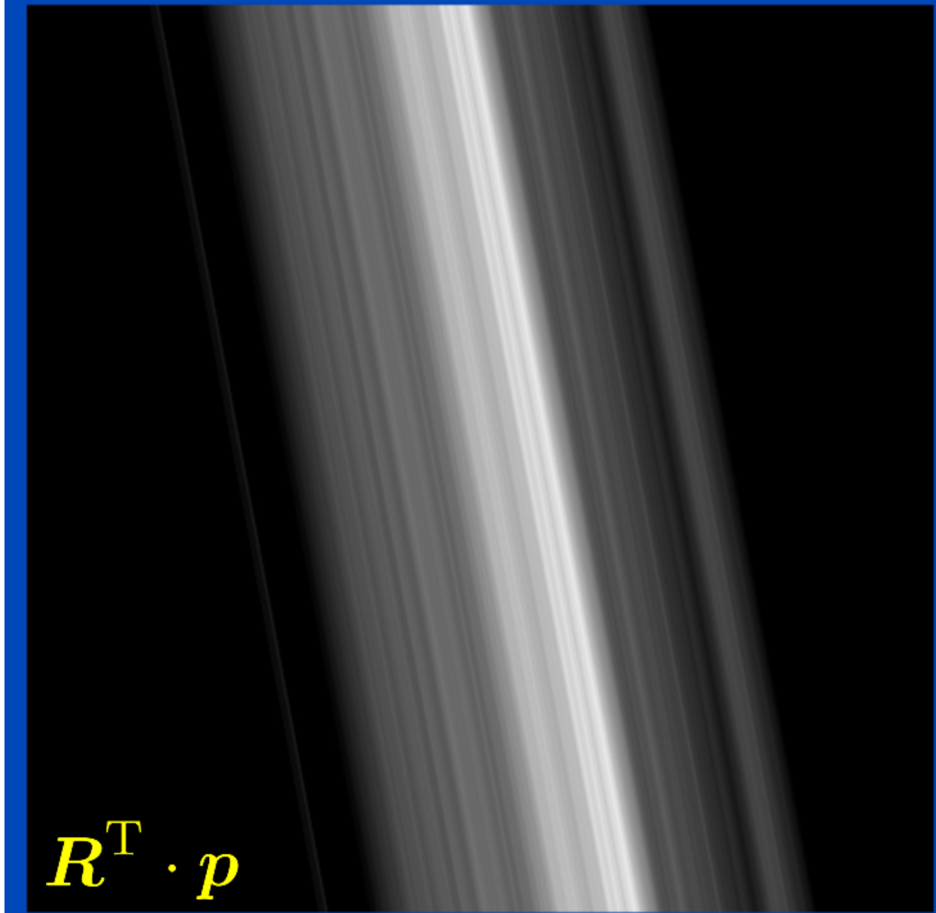
apply inverse model

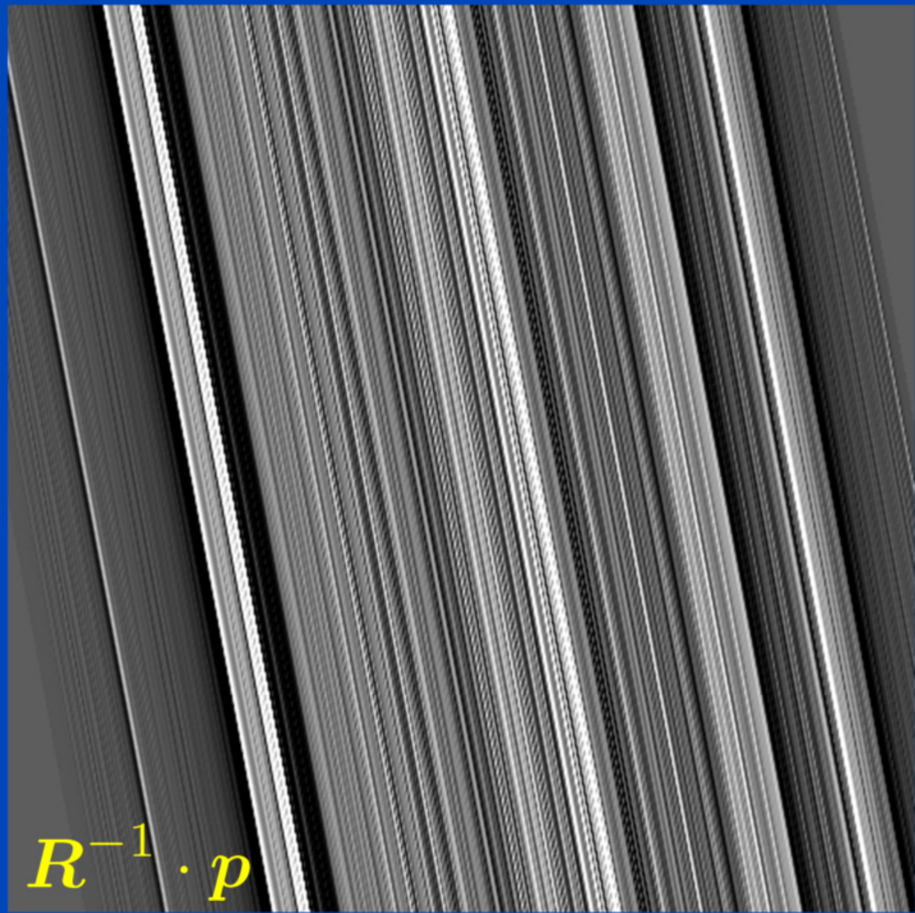


apply forward model

$$f_{\nu+1} = f_\nu + R^{\mathrm{T}} \cdot \frac{p - R \cdot f_\nu}{R^2 \cdot 1}$$

Direct vs. Filtered Backprojection





Flavours of Iterative Reconstruction

- **ART** $$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{R}^{\mathrm{T}} \cdot \frac{\boldsymbol{p} - \boldsymbol{R} \cdot \boldsymbol{f}_\nu}{\boldsymbol{R}^2 \cdot \boldsymbol{1}}$$

- **SART** $$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \frac{1}{\boldsymbol{R}^{\mathrm{T}} \cdot \boldsymbol{1}} \boldsymbol{R}^{\mathrm{T}} \cdot \frac{\boldsymbol{p} - \boldsymbol{R} \cdot \boldsymbol{f}_\nu}{\boldsymbol{R} \cdot \boldsymbol{1}}$$

- **MLEM** $$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu \frac{\boldsymbol{R}^{\mathrm{T}} \cdot \left(e^{-\boldsymbol{R} \cdot \boldsymbol{f}_\nu}\right)}{\boldsymbol{R}^{\mathrm{T}} \cdot \left(e^{-\boldsymbol{p}}\right)}$$

- **OSC** $$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_\nu + \boldsymbol{f}_\nu \frac{\boldsymbol{R}^{\mathrm{T}} \cdot \left(e^{-\boldsymbol{R} \cdot \boldsymbol{f}_\nu} - e^{-\boldsymbol{p}}\right)}{\boldsymbol{R}^{\mathrm{T}} \cdot \left(e^{-\boldsymbol{R} \cdot \boldsymbol{f}_\nu} \boldsymbol{R} \cdot \boldsymbol{f}_\nu\right)}$$

- **and hundreds more …**

Iterative Reconstruction: Parameters

- Image/object representation
  - Pixel centers
  - Pixel area
  - Blobs
  - Sampling density (pixel size, pixel locations, …)

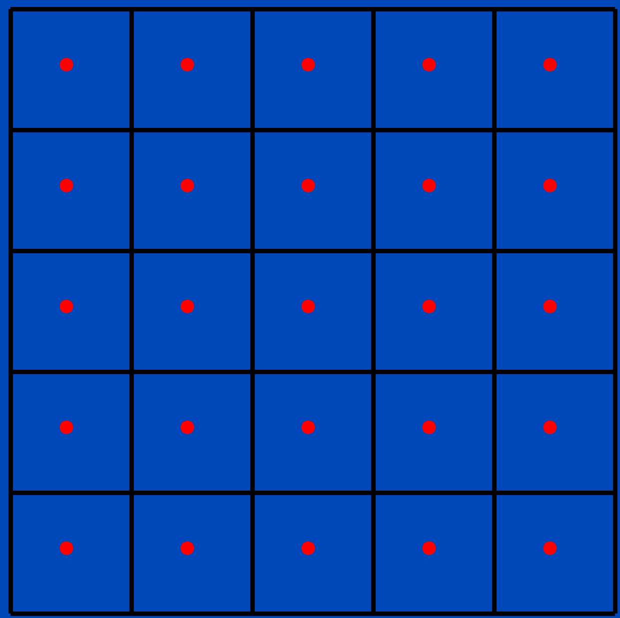
$$f(x,y)=\sum_m f_m b(x-x_m,y-y_m)$$

- Forward model (forward projection)
  - Joseph-type, Bresenham-type, distance-driven-type, …
  - Needle beam (infinitely thin ray), many needle beams per ray, …
  - Beam shape (varying beam cross-section, angular blurring, …)
  - Physical effects (beam hardening, scatter, motion, detector sensitivity, non-linear partial volume effect, …)
- Objective function, update equation
  - Statistical model (Gaussian, Poisson, shifted Poisson, …)
  - Regularisation (edge-preserving, …)
  - Artifact reduction

$$C(f)=\left(\boldsymbol{R}\cdot \boldsymbol{f}-\boldsymbol{p}\right)^2$$

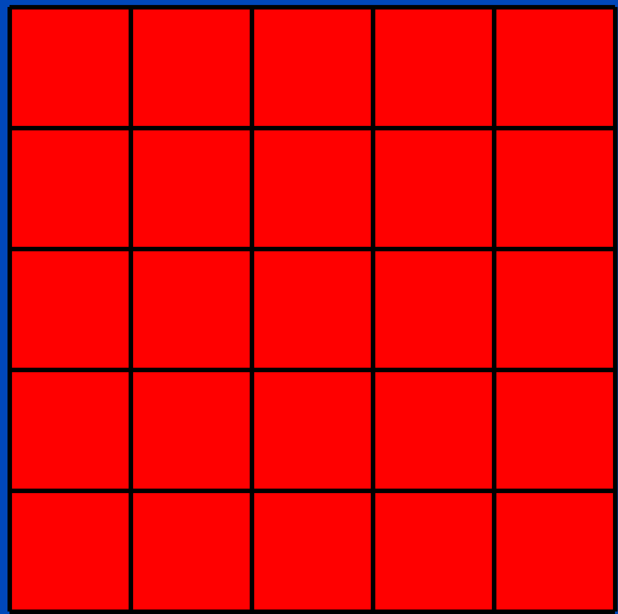
- Inverse model (backprojection)
  - Transpose of forward model
  - Pixel-driven backprojection
  - Filtered backprojection
  - …

Image Representation



$$b(x, y) = \bullet$$

Image Representation



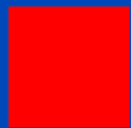
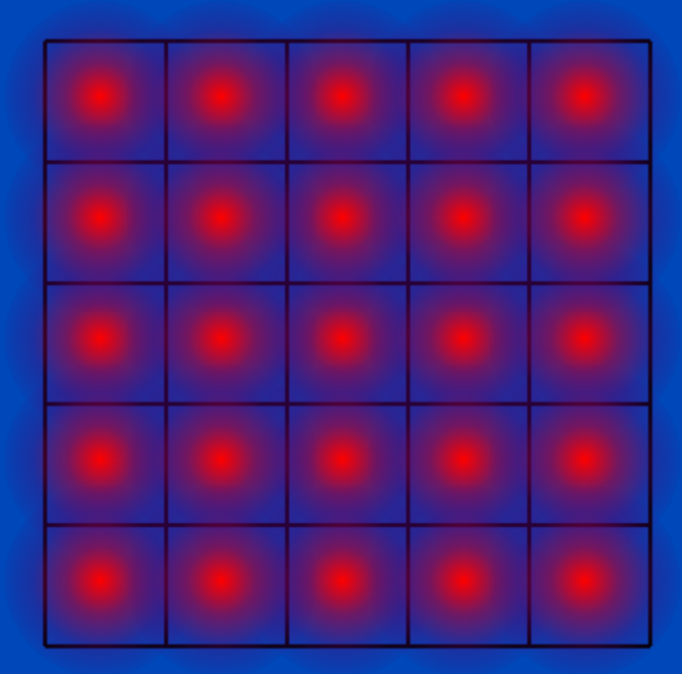
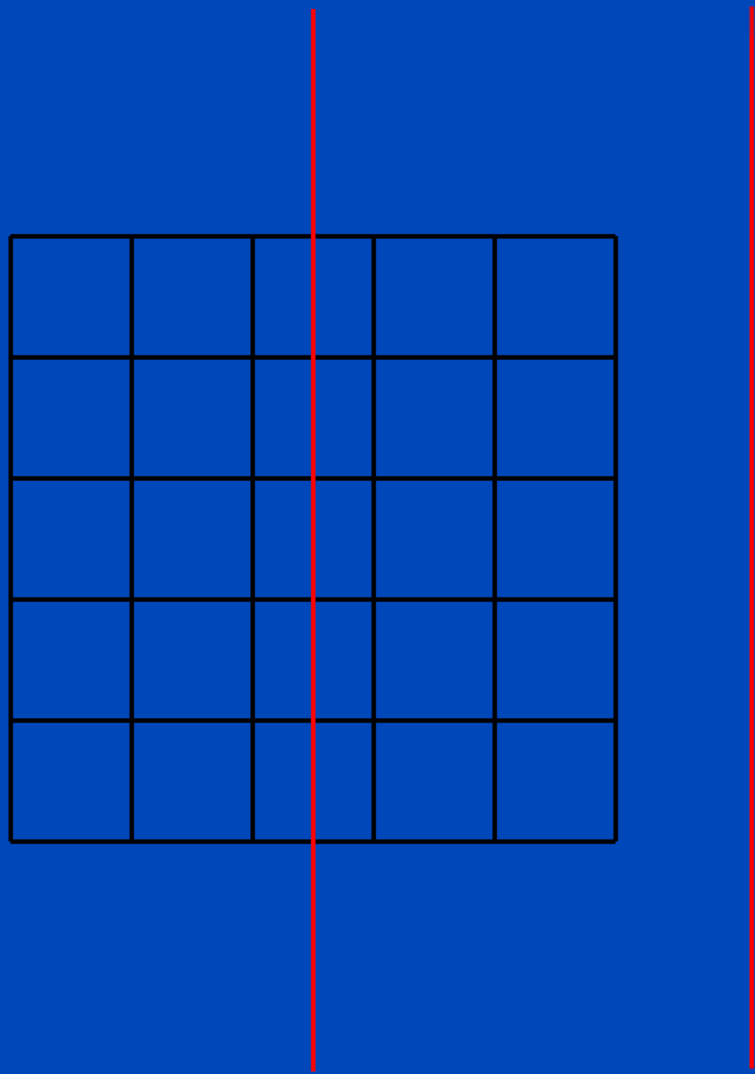
$b(x, y) =$ 

Image Representation

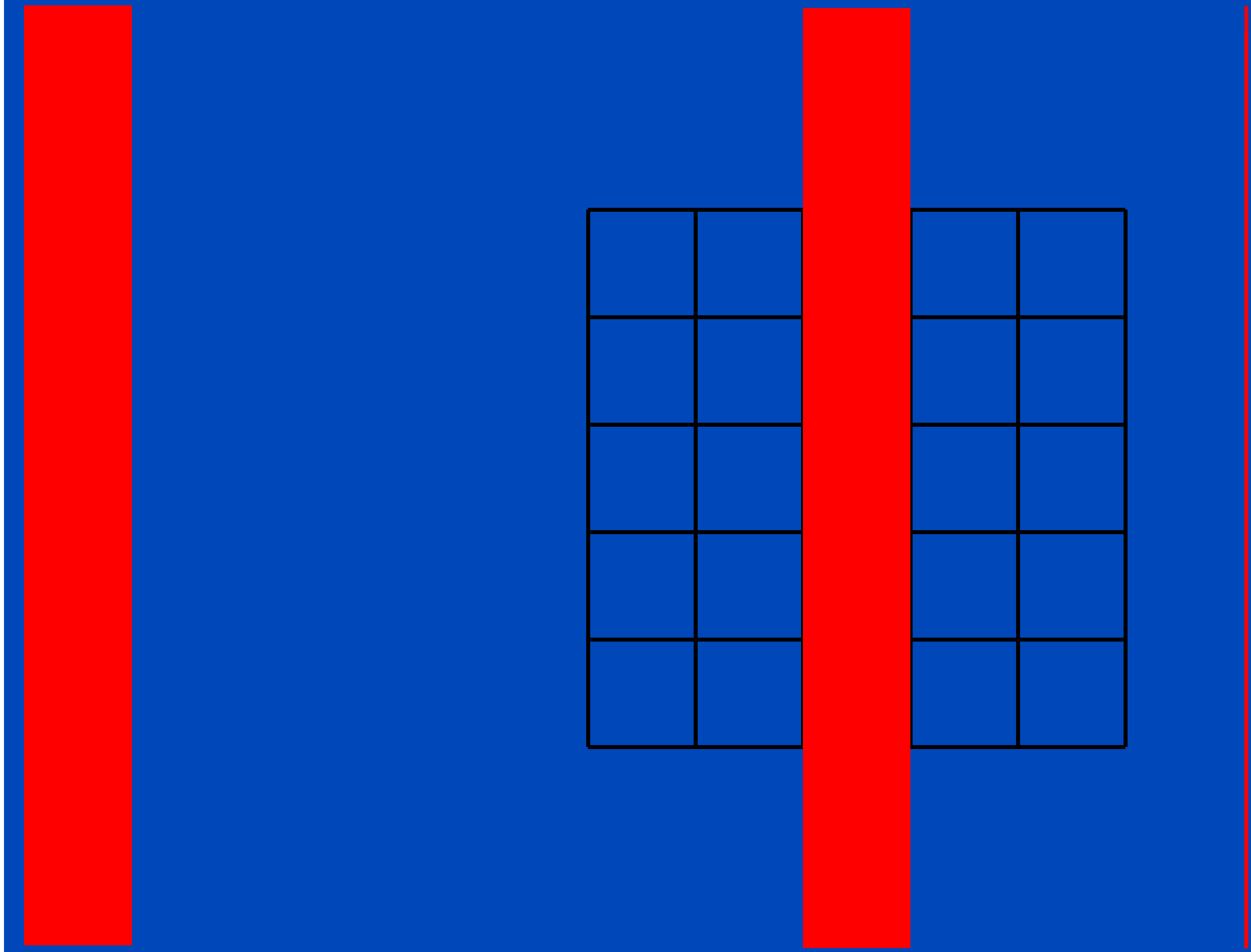


$b(x, y) =$ 

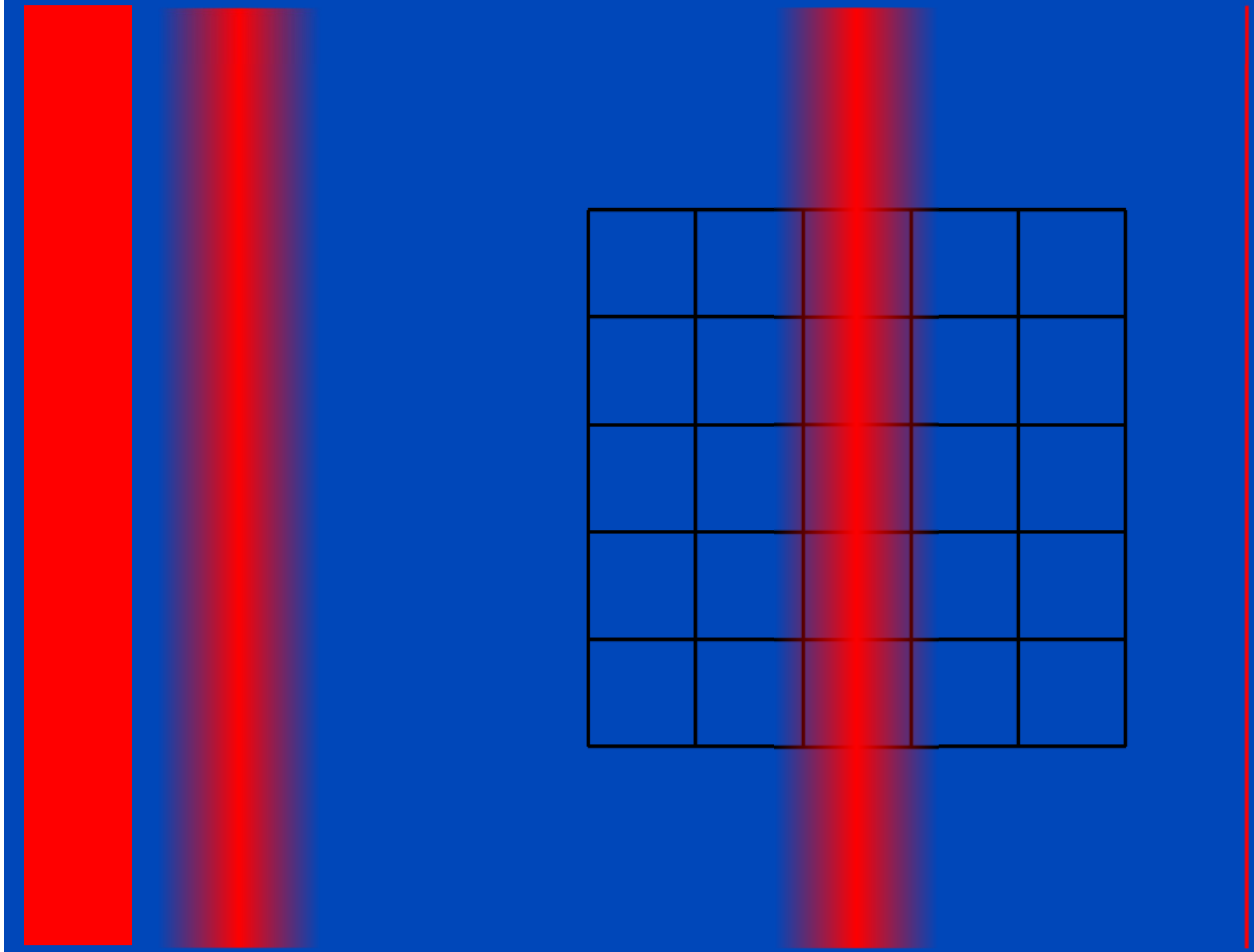
Forward Model: Beam Shape



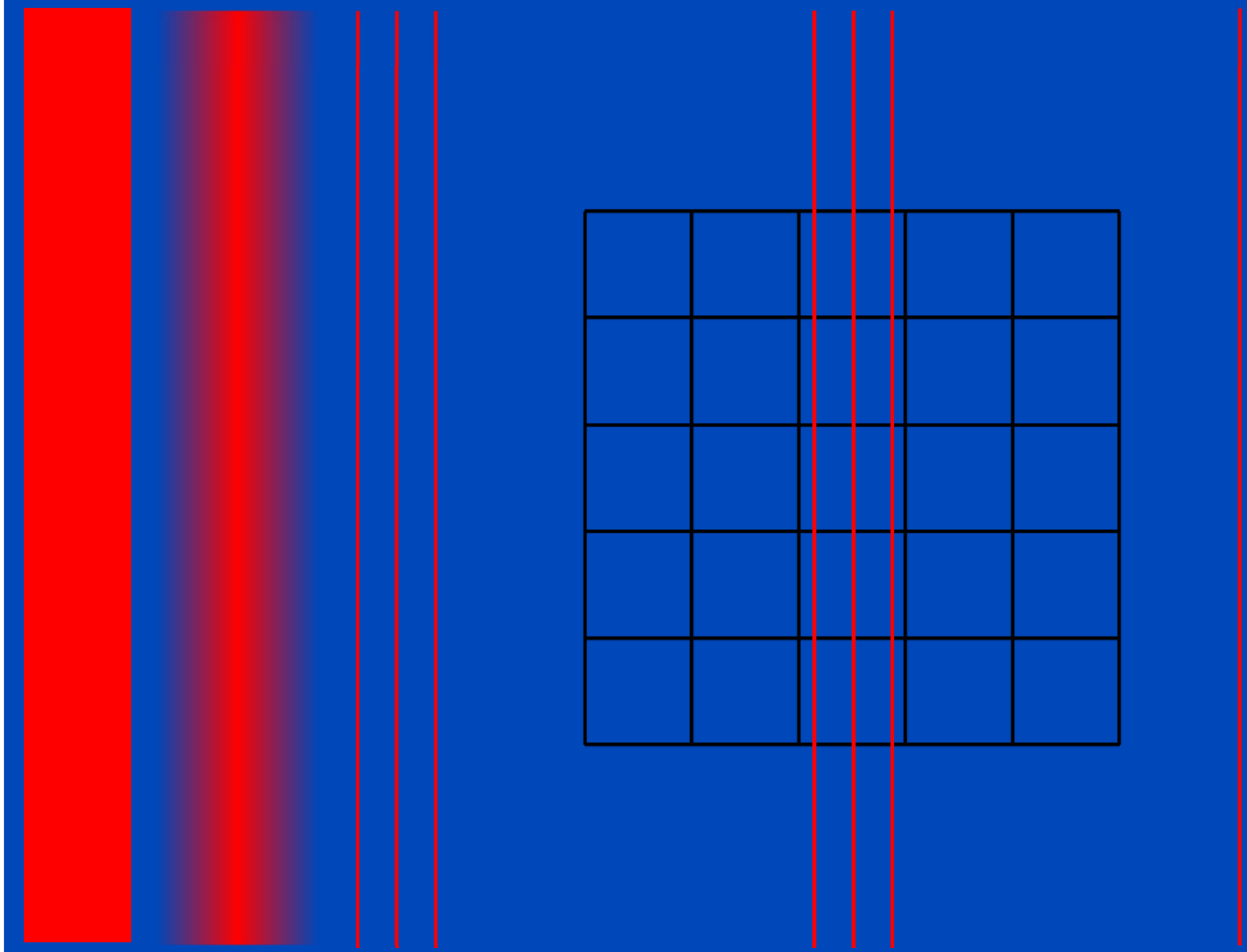
Forward Model: Beam Shape



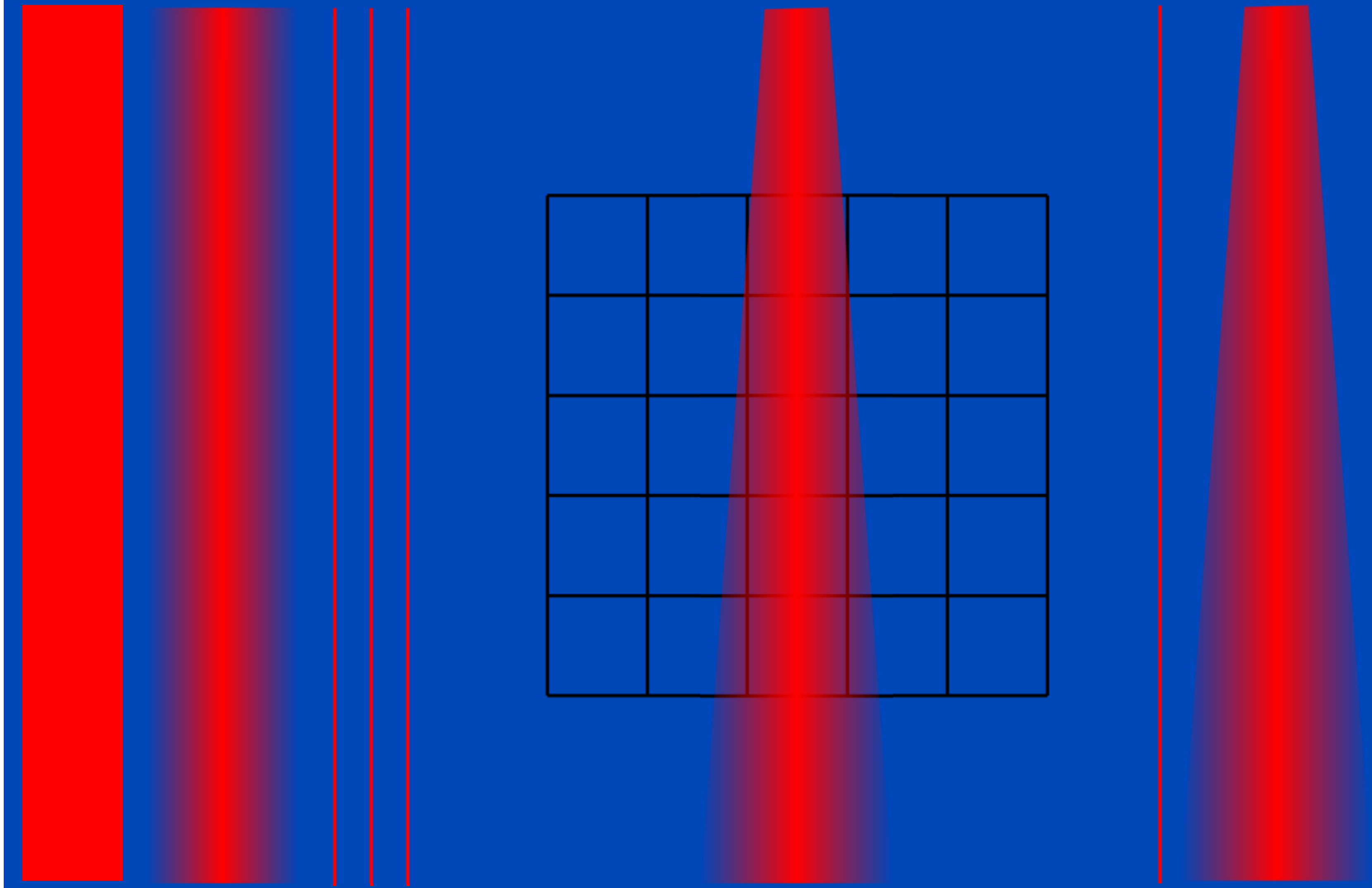
Forward Model: Beam Shape



Forward Model: Beam Shape



Forward Model: Beam Shape



Forward Model: Beam Shape

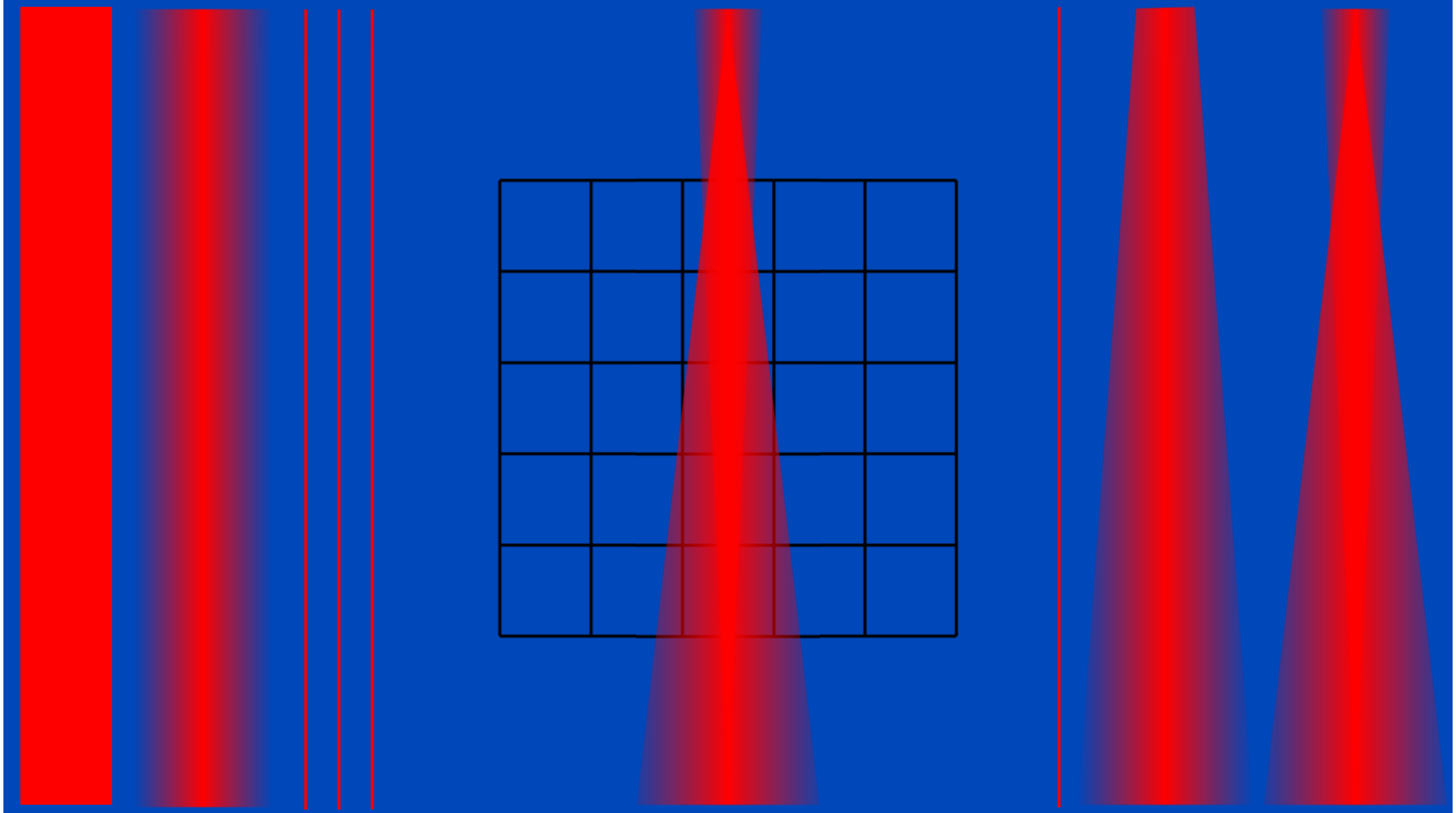
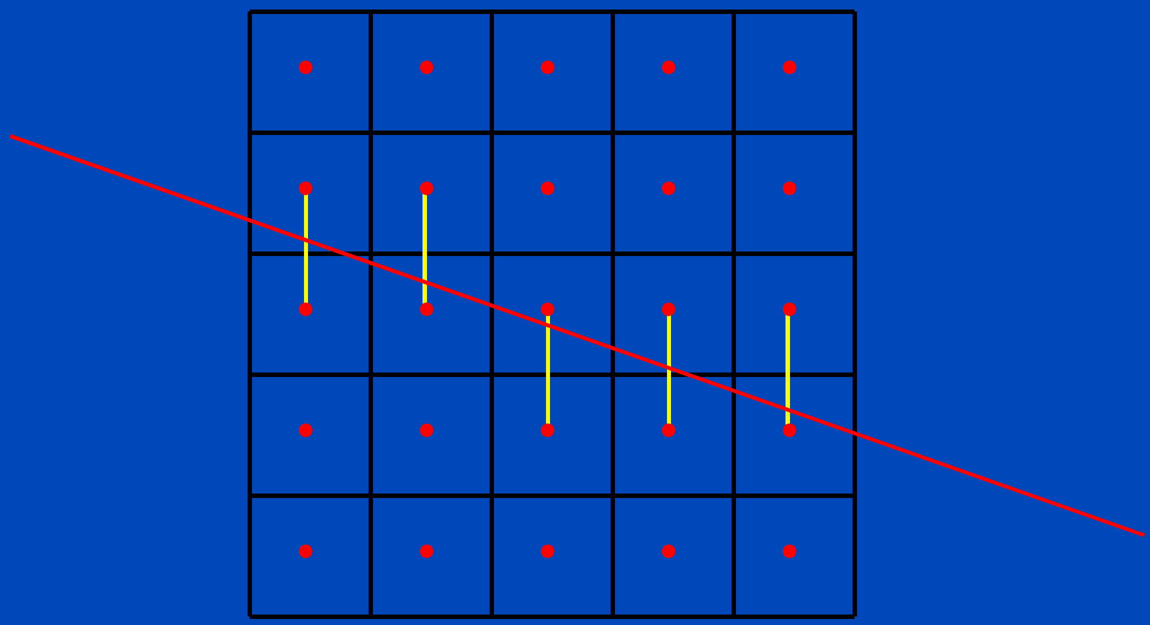


Image Representation and Forward Model are Linked!



Joseph's forward projector

What Makes Iterative Recon Attractive?

- No need to find an analytical solution
- Works for all geometries with only small adaptations
- Allows to model any effect
- Allows to incorporate prior knowledge
  - noise properties (quantum noise, electronic noise, noise texture, …)
  - prior scans (e.g. planning CT, full scan data, …)
  - image properties such as smoothness, edges (e.g. minimum TV)
  - …
- Handles missing data implicitly (but not necessarily better)

[1]L. Ritschl, S. Sawall, M. Knaup, A. Hess, and M. Kachelrieß, Phys. Med. Biol. 57, Jan. 2012

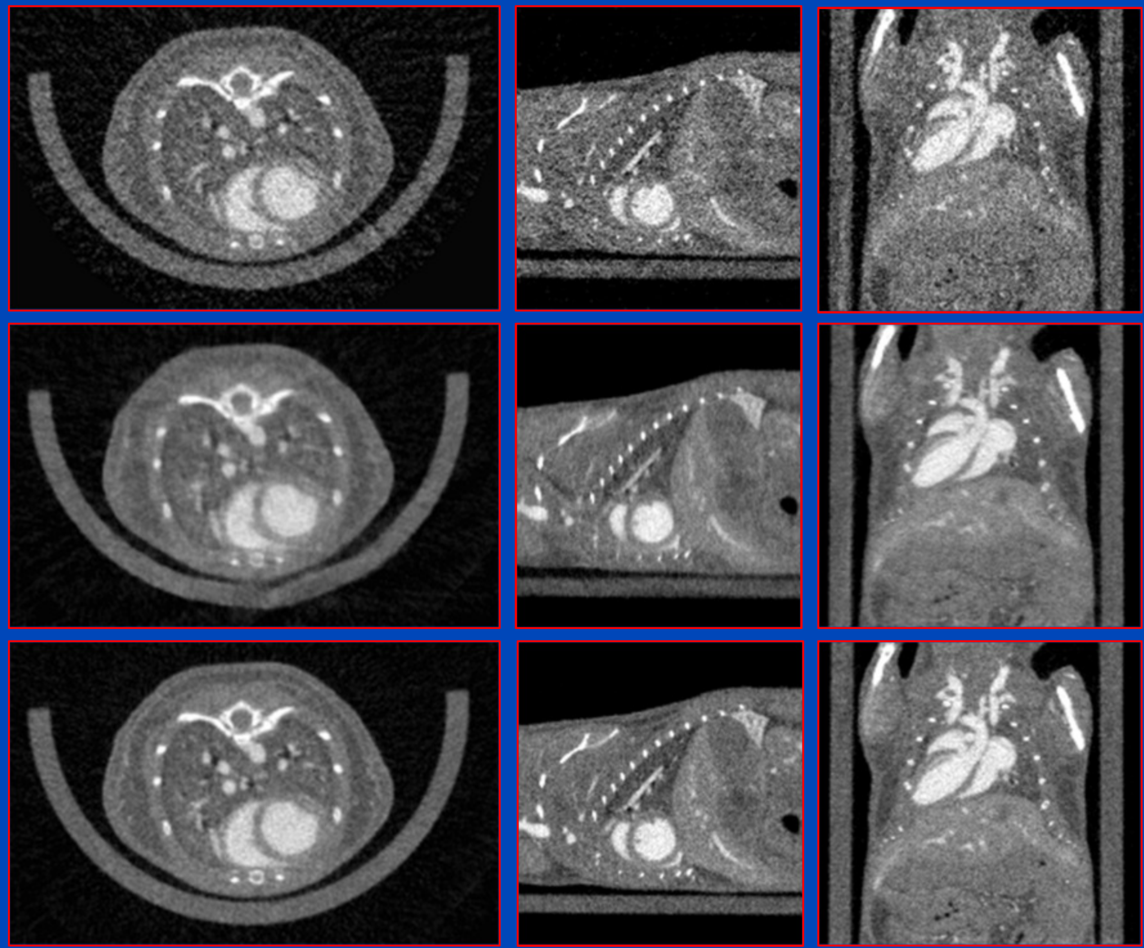
Cardiac Cycle of a Mouse

Axial | Sagittal | Coronal

PC-FDK

iTV[1]

HDTV[2]

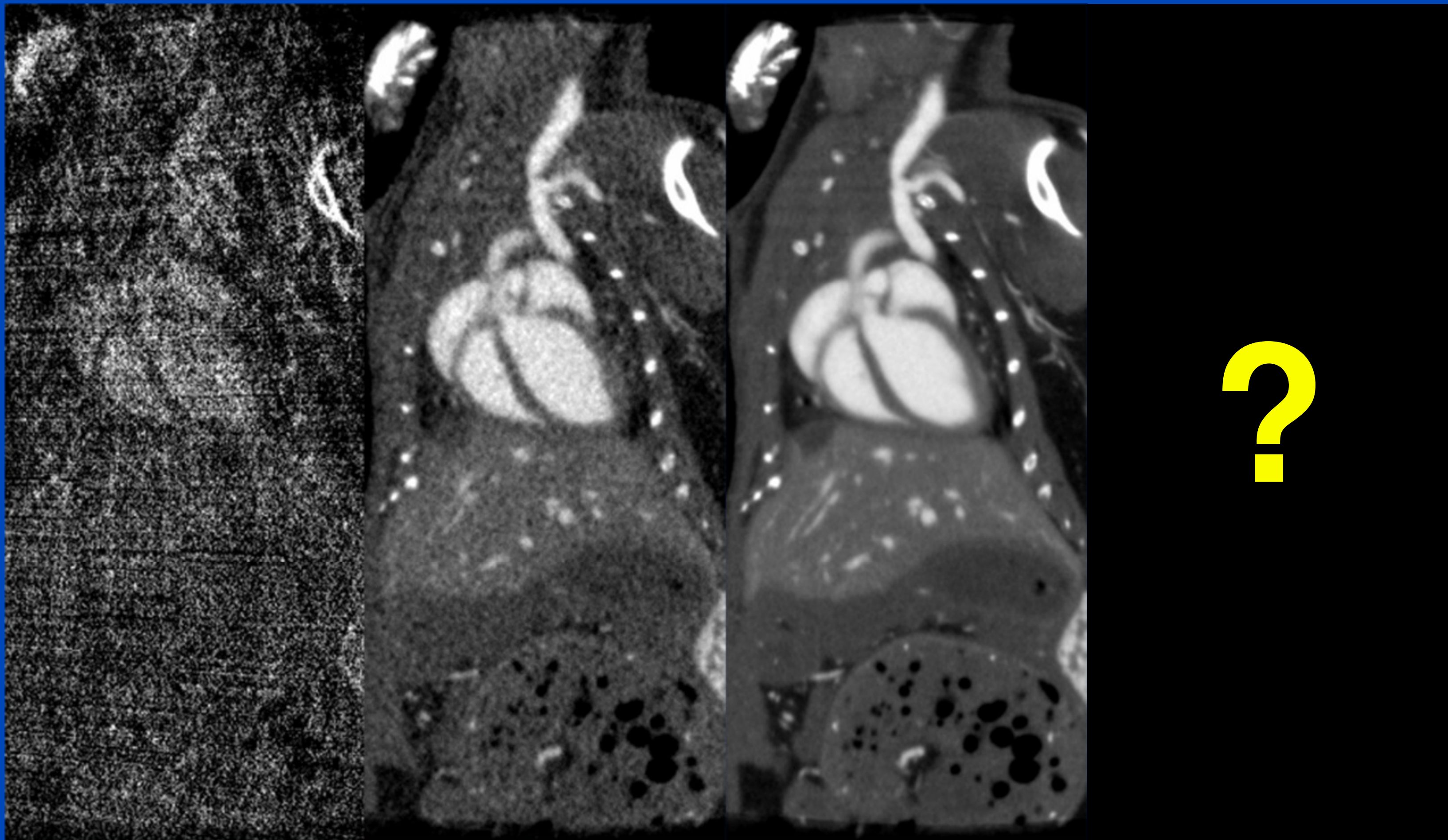


Cardiac Gating : ΔC=10%
Image window: C=0 HU / W=1200 HU

[1]L. Ritschl, F. Bergner, C. Fleischmann, and M. Kachelrieß, Phys. Med. Biol. 56, Feb. 2012
[2]L. Ritschl, S. Sawall, M. Knaup, A. Hess, and M. Kachelrieß, Phys. Med. Biol. 57, Jan. 2012

Generations of Reconstruction

2007 (analytical)	2011 (iterative)	2015 (MoCo)	2020 (????)



voxels are stationary

voxels may move

C = 400 HU, *W* = 1400 HU

Downsides

- Classical iterative recon is slow!
- Classical iterative recon cannot do small FOVs.
- There are many open parameters.
- The reconstruction is non-linear.
- Can we trust the images?

Ordered Subsets

- Divide one iteration into S sub-iterations.
- Each of these S subsets covers N/S projections.
- During one iteration all subsets and therefore all projections are used exactly once.
- Per iteration the volume is updated S times (once per sub-iteration).
- An up to S-fold speed-up can be observed.

Ordered Subsets
Illustration for *N* = 32 Projections

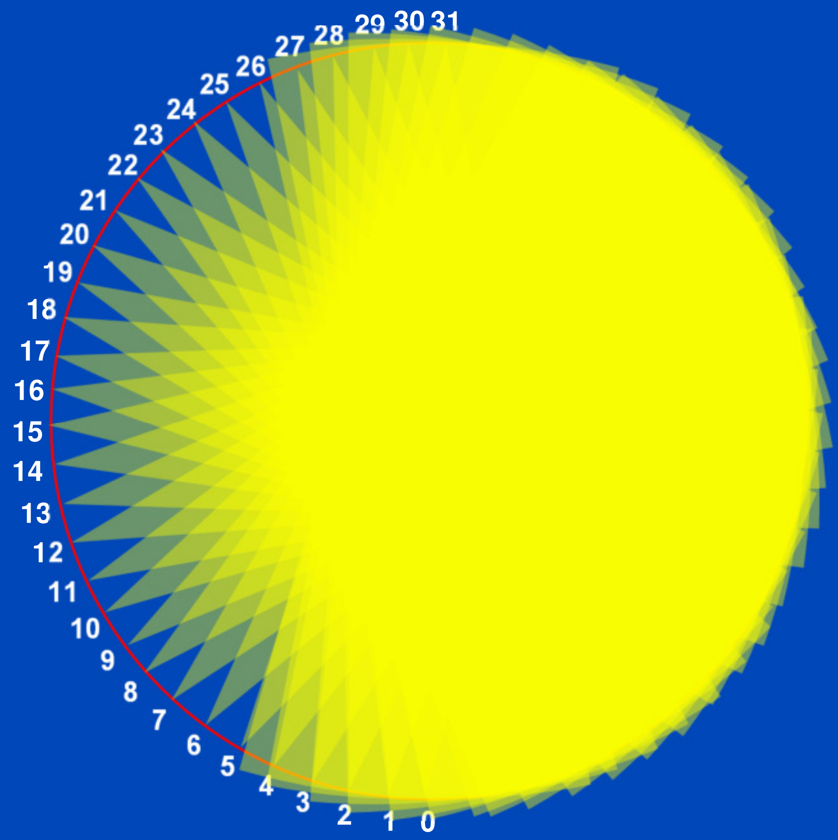
Conventional procedure without subsets (*S* = 1)

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31

Ordered subsets with *S* = 8 sub-iterations (4 projections per subset)

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31

Ordered Subsets



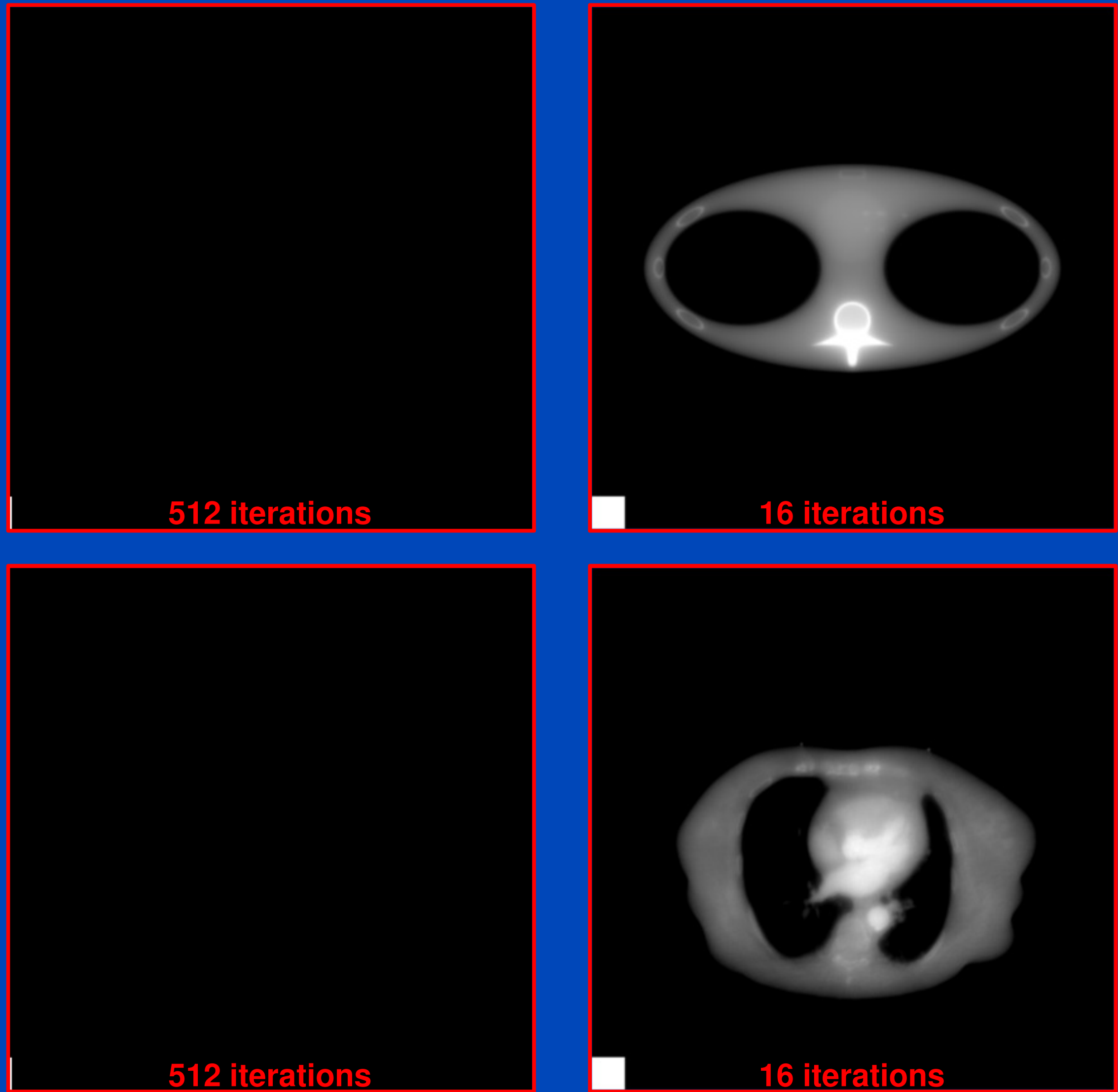
N **= 32,** ***S*** **= 8, i.e. 4 projections per subset**

Sequence Can be Generated Using Simple Bit Reversal

0	->	0
1	->	16
2	->	8
3	->	24
4	->	4
5	->	20
6	->	12
7	->	28
8	->	2
9	->	18
10	->	10
11	->	26
12	->	6
13	->	22
14	->	14
15	->	30
16	->	1
17	->	17
18	->	9
19	->	25
20	->	5
21	->	21
22	->	13
23	->	29
24	->	3
25	->	19
26	->	11
27	->	27
28	->	7
29	->	23
30	->	15
31	->	31

Using Ordered Subsets Makes it Faster!

S = 1 (no subsets) | *S* = 32 (ordered subsets)



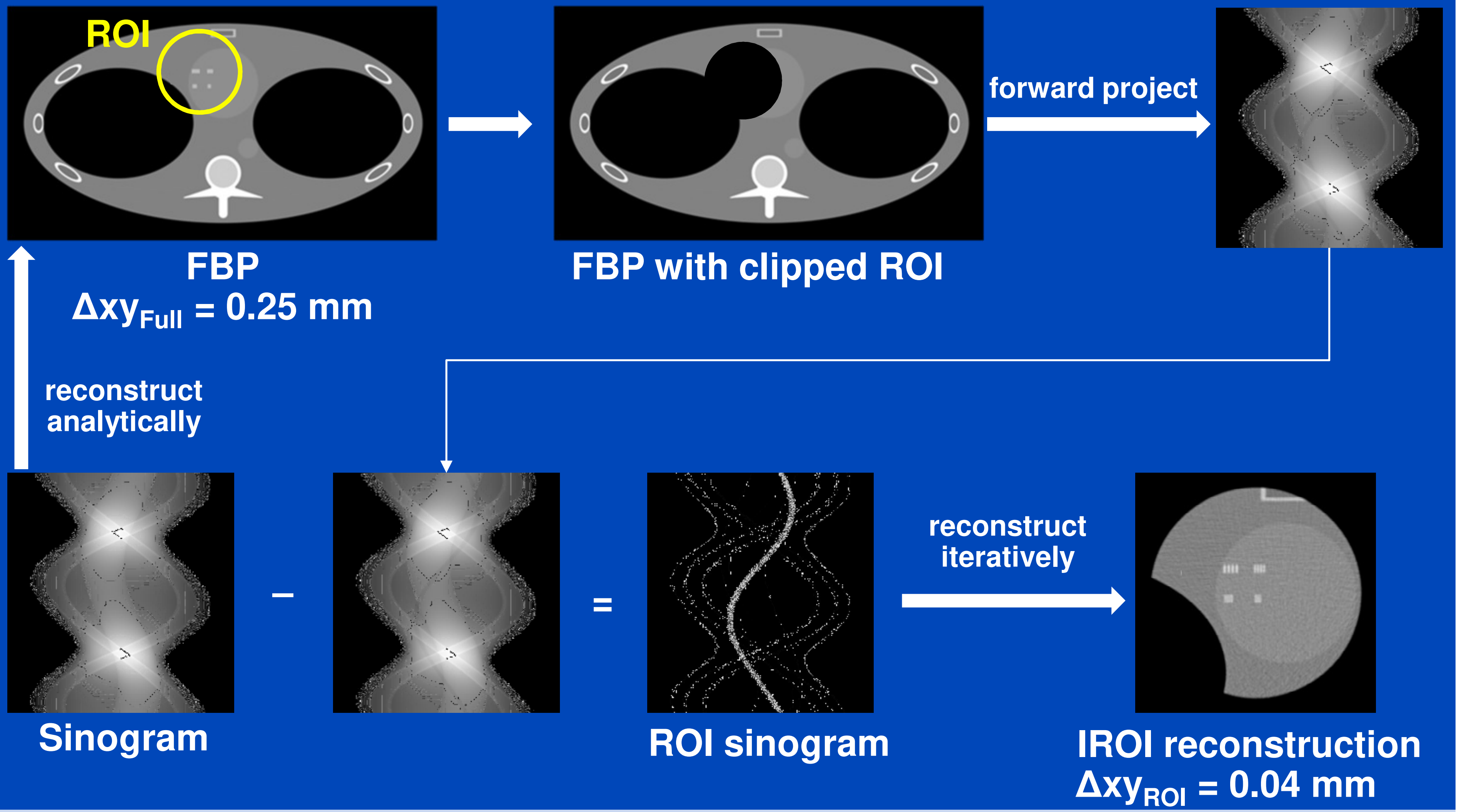
C = 0 HU, *W* = 1000 HU

Image Updates

S = 1 (no subsets) | S = 32 (ordered subsets)

C = 0 HU, W = 1000 HU

Reconstructing Small FOVs



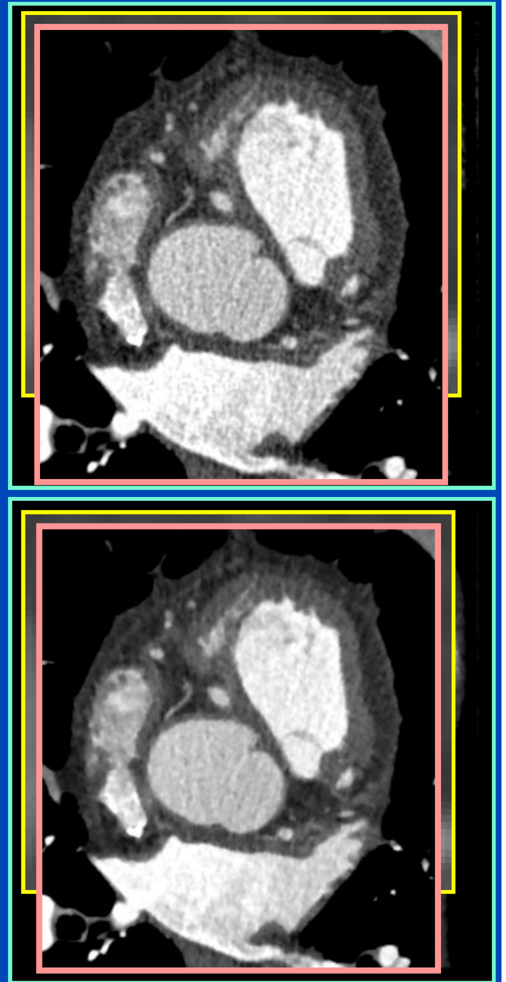
A. Ziegler, T. Nielsen, and M. Grass, “Iterative Reconstruction of Region of Interest for Transmission Tomography”, Med. Phys. 35 (4), Mar. 2008

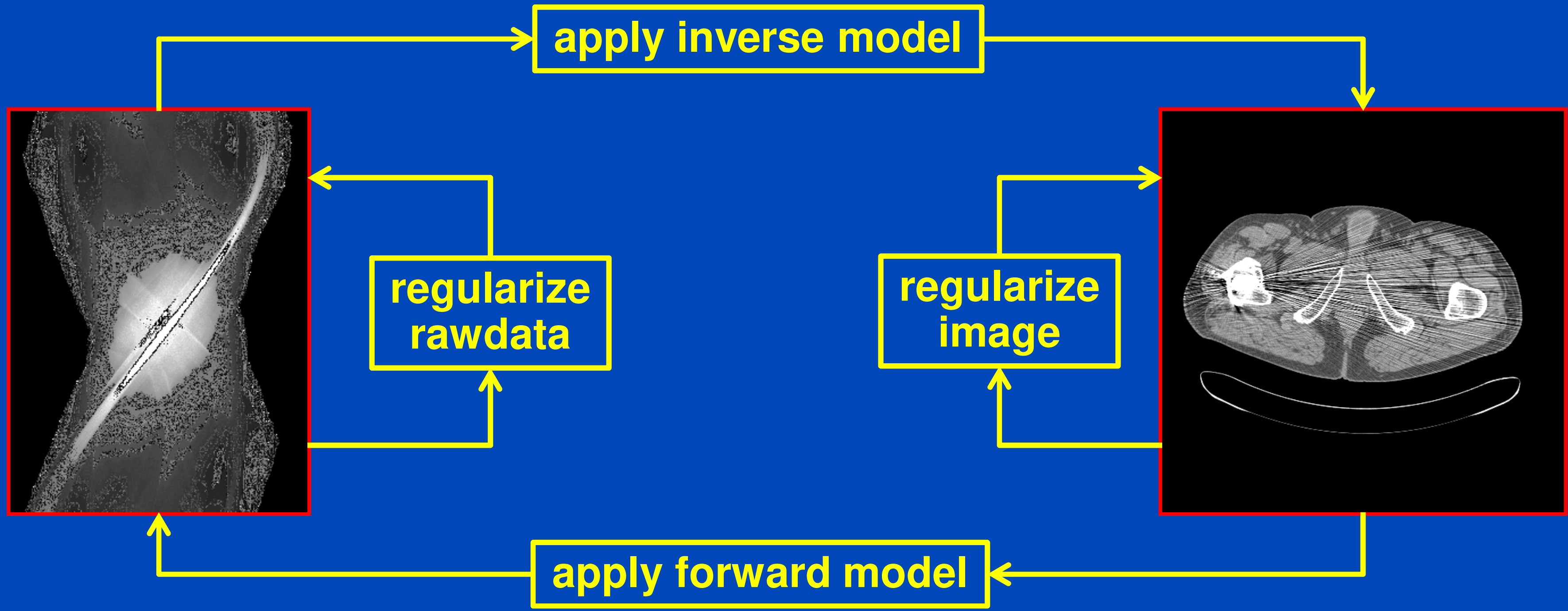
Practical Ways to do it Iterative

- In many cases artifact correction is iterative
  - Higher order beam hardening correction
  - Cone-beam artifact correction
  - Scatter correction
- Practical “iterative reconstruction” approaches
  - often use empirical solutions
  - combine iterative with analytical reconstruction
  - combine iterative or analytical reconstruction with image restoration

Iterative Reconstruction

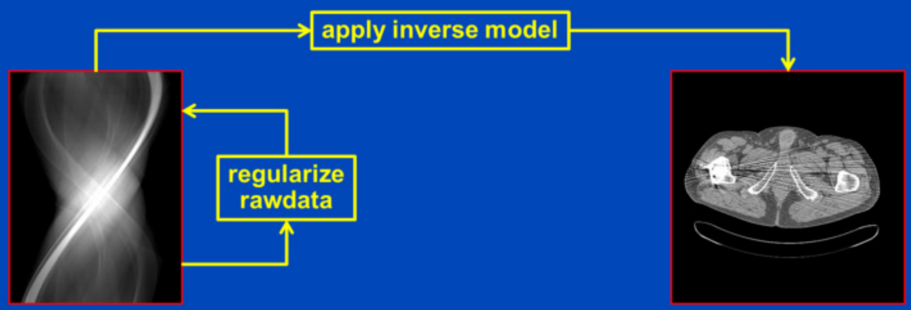
- Aim: less artifacts, lower noise, lower dose
- Iterative reconstruction
  - Reconstruct an image.
  - Does the image correspond to the rawdata?
  - If not, reconstruct a correction image and continue.
- SPECT + PET are iterative for a long time!
- CT product implementations
  - ASIR (adaptive statistical iterative reconstruction, GE)
  - iDose (Philips)
  - IRIS (image reconstruction in image space, Siemens)
  - AIDR 3D (adaptive iterative dose reduction, Toshiba)
  - VEO, MBIR (model-based iterative reconstruction, GE)
  - IMR (iterative model reconstruction, Philips)
  - SAFIRE, ADMIRE (advanced modeled iterative reconstruction, Siemens)
  - FIRST (forward projected model-based iterative reconstruction solution, Toshiba)



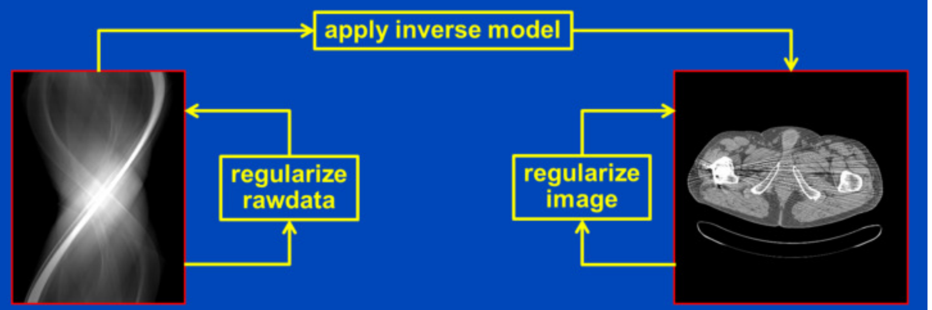


- Rawdata regularization: adaptive filtering[1], precorrections, filtering of update sinograms...
- Inverse model: backprojection (R^T) or filtered backprojection (R^{-1}). In clinical CT, where the data are of high fidelity and nearly complete, one would prefer filtered backprojection to increase convergence speed.
- Image regularization: edge-preserving filtering. It may model physical noise effects (amplitude, direction, correlations, …). It may reduce noise while preserving edges. It may include empirical corrections.
- Forward model (R_{phys}): Models physical effects. It can reduce beam hardening artifacts, scatter artifacts, cone-beam artifacts, noise, …

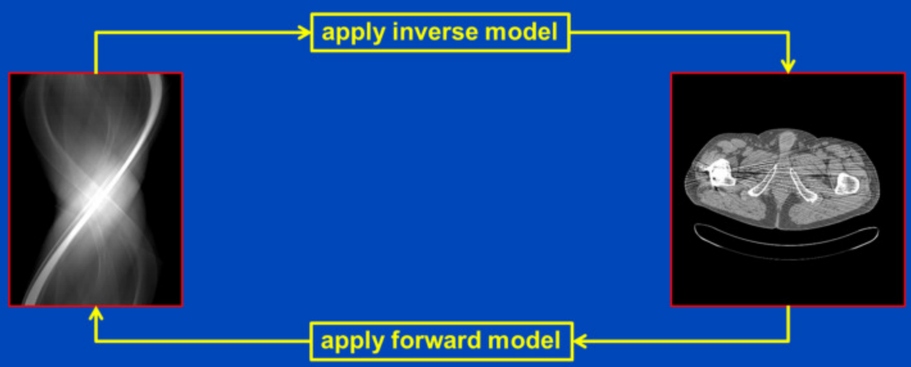
[1]M. Kachelrieß et al., Generalized Multi-Dimensional Adaptive Filtering, MedPhys 28(4), 2001



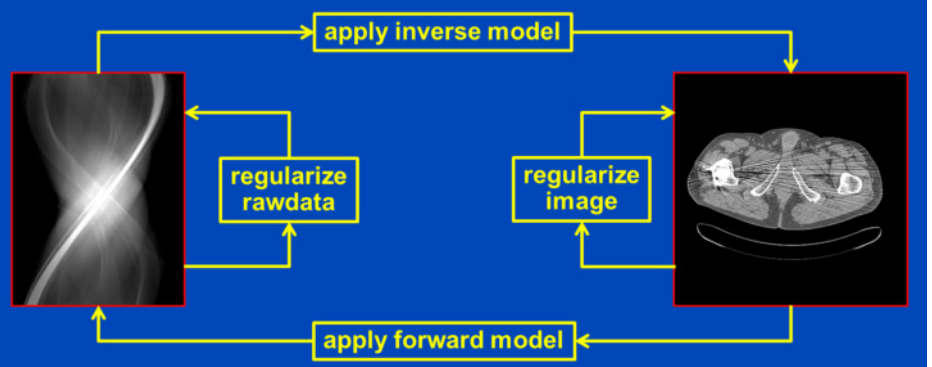
Conventional FBP with rawdata denoising (all vendors)



AIDR3D (Canon), ASIR, ASIR-V (Ge), IRIS (Siemens), iDose (Philips), SnapShot Freeze (GE), iTRIM (Siemens)

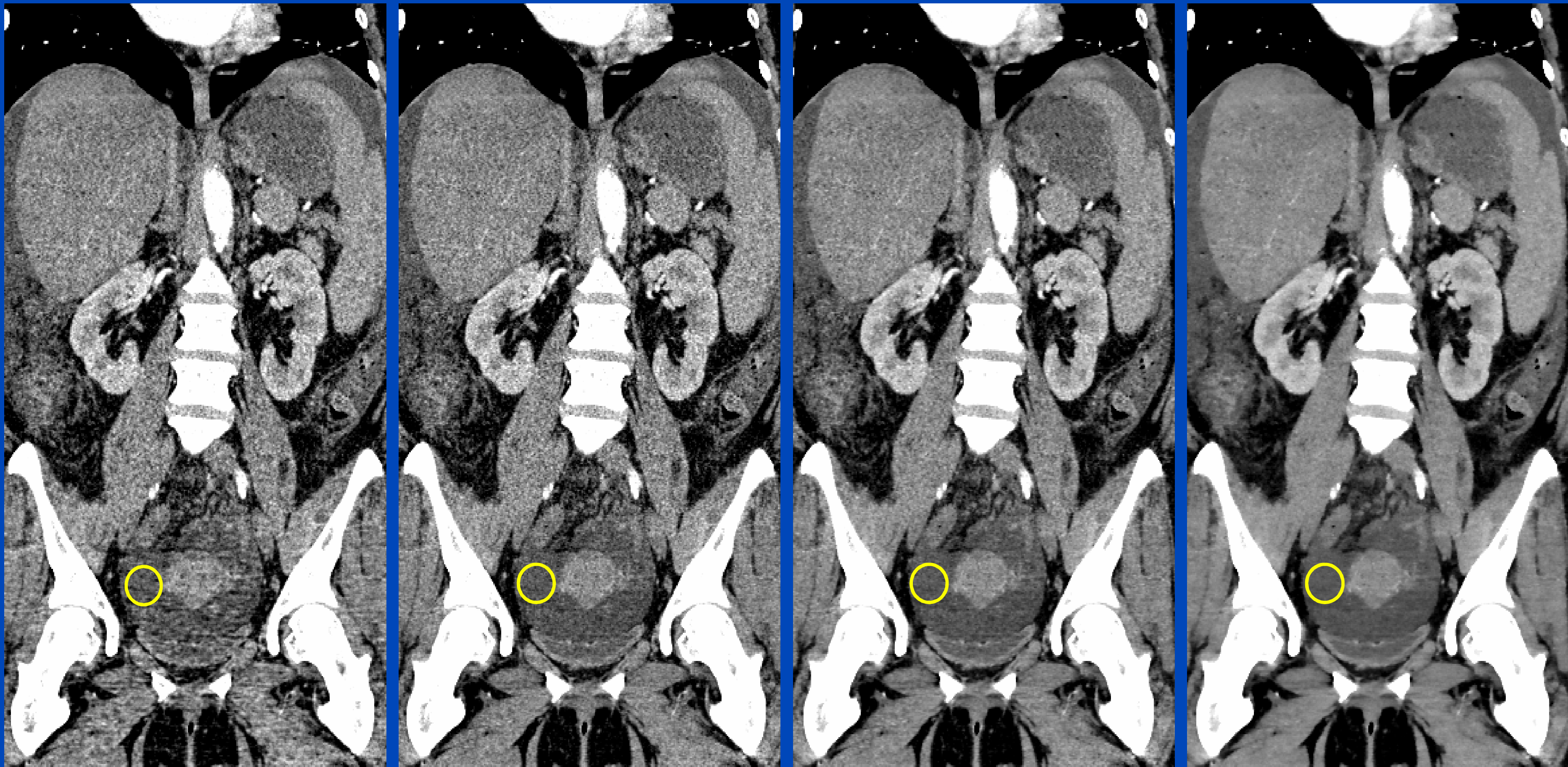


Veo123/MBIR (Ge)

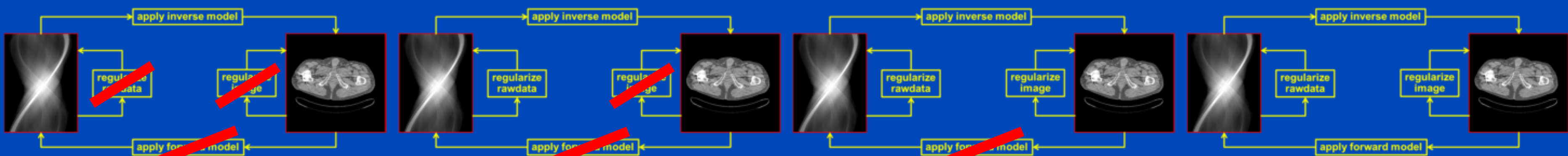


FIRST (Canon), IMR (Philips), SAFIRE, ADMIRE (Siemens)

Plain FBP	Siemens Standard	IRIS VA34	SAFIRE VA40

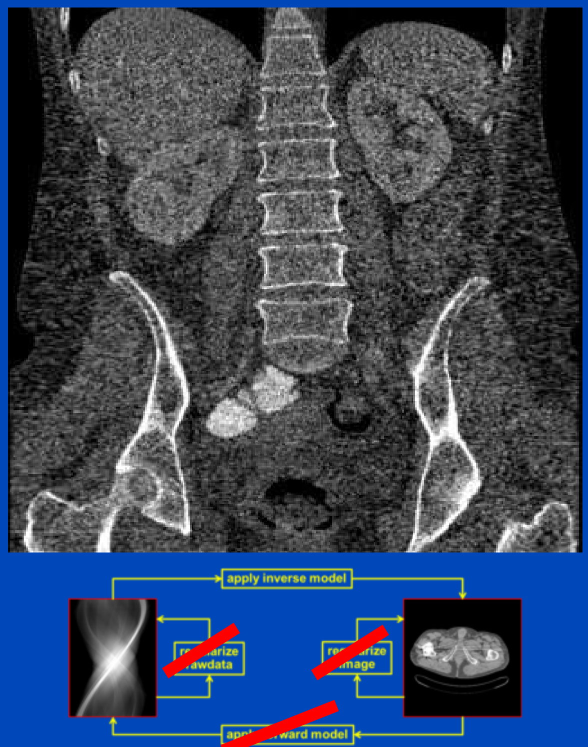


σ = 26.8 HU	σ = 17.6 HU	σ = 12.3 HU	σ = 7.8 HU

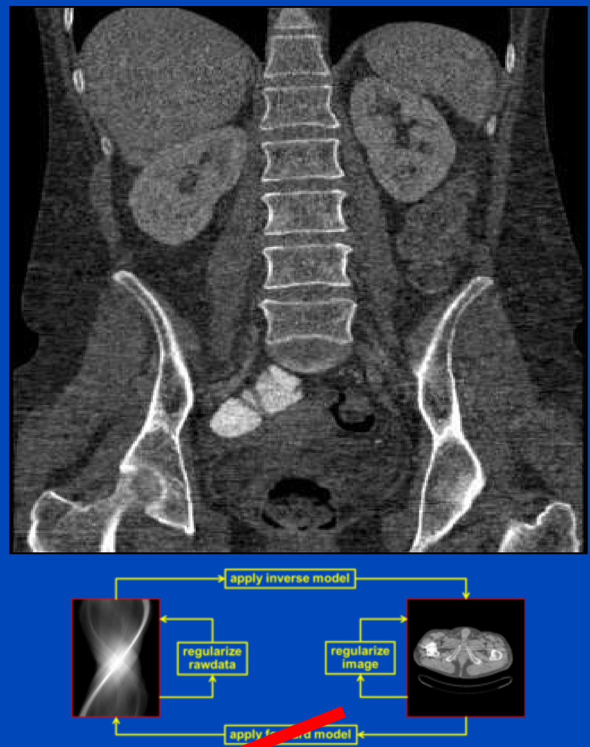


CT images provided by Siemens Healthcare, Forchheim, Germany

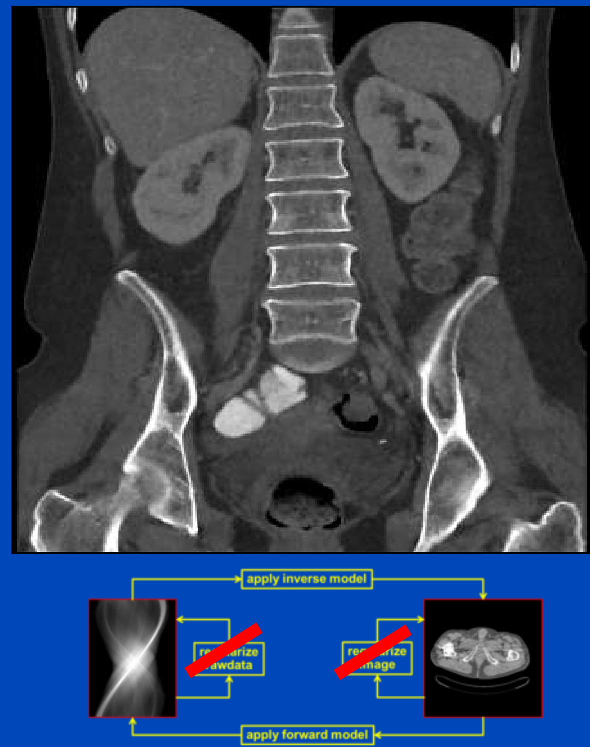
FBP



ASIR

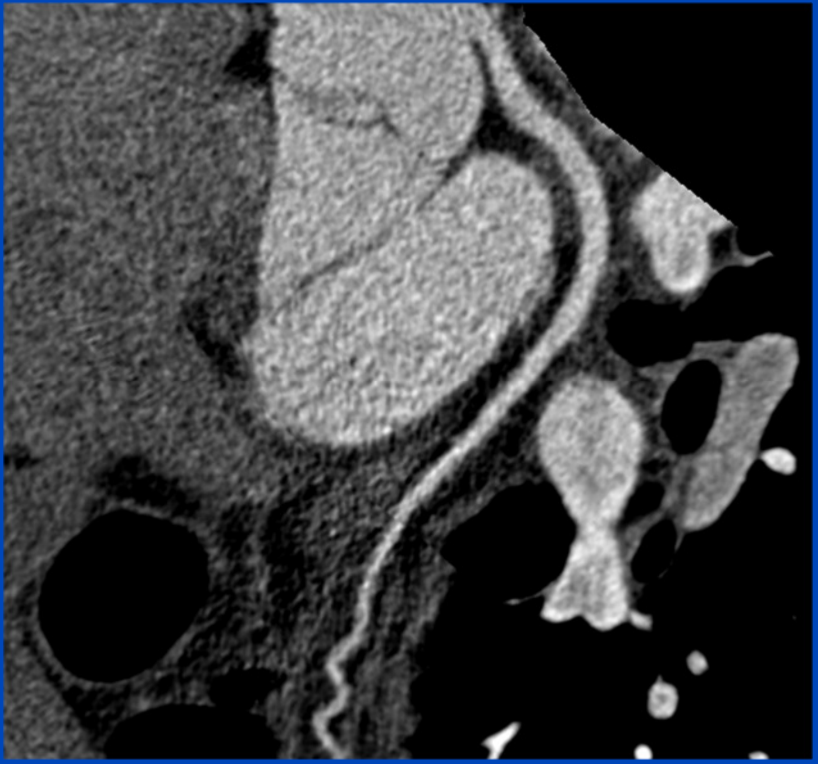


Veo

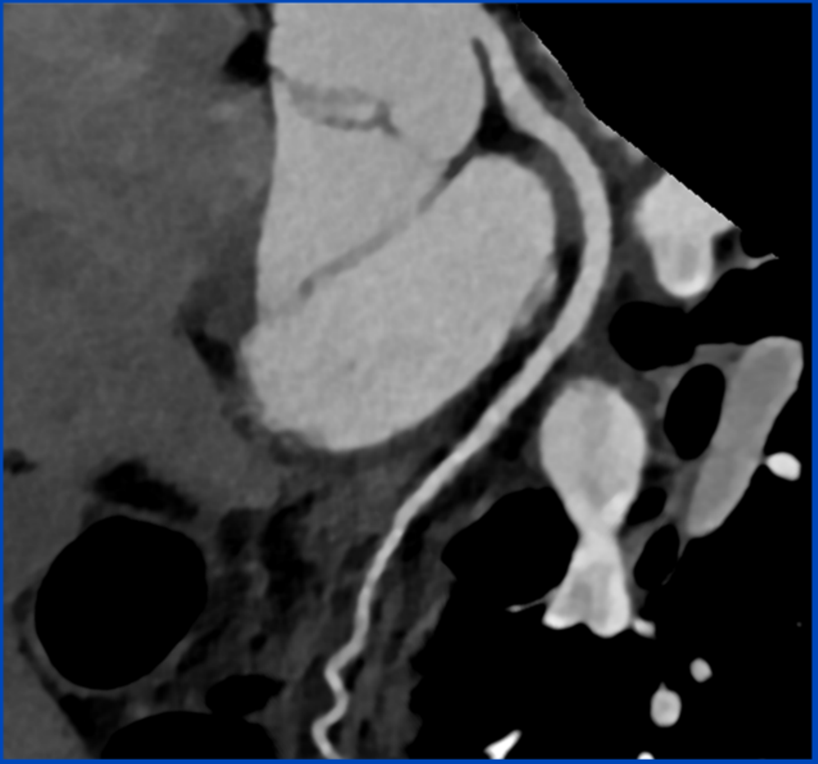


Courtesy of Dr. Jiang Hsieh, GE Healthcare Technologies, WI, USA.

FBP

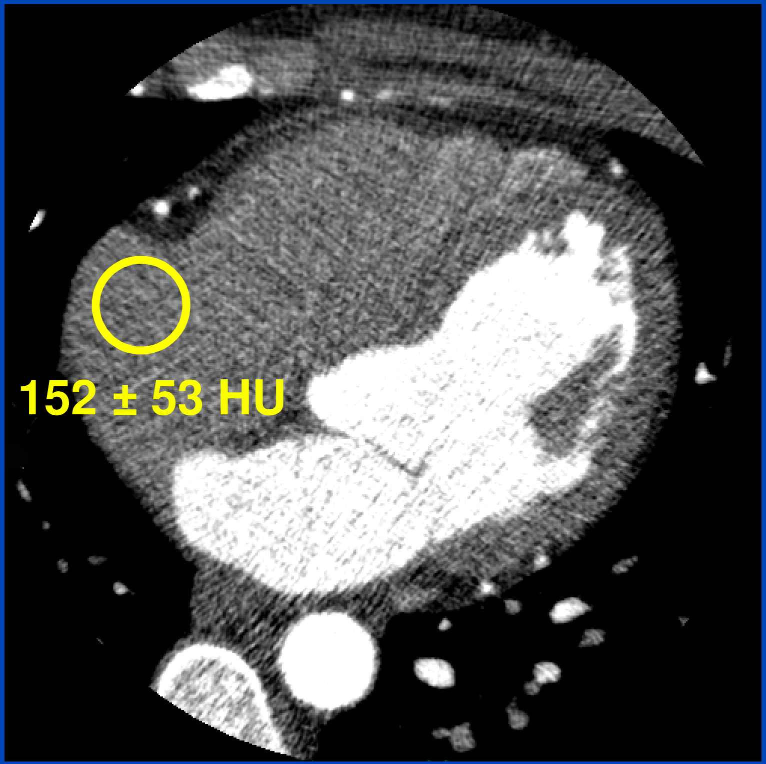


IMR

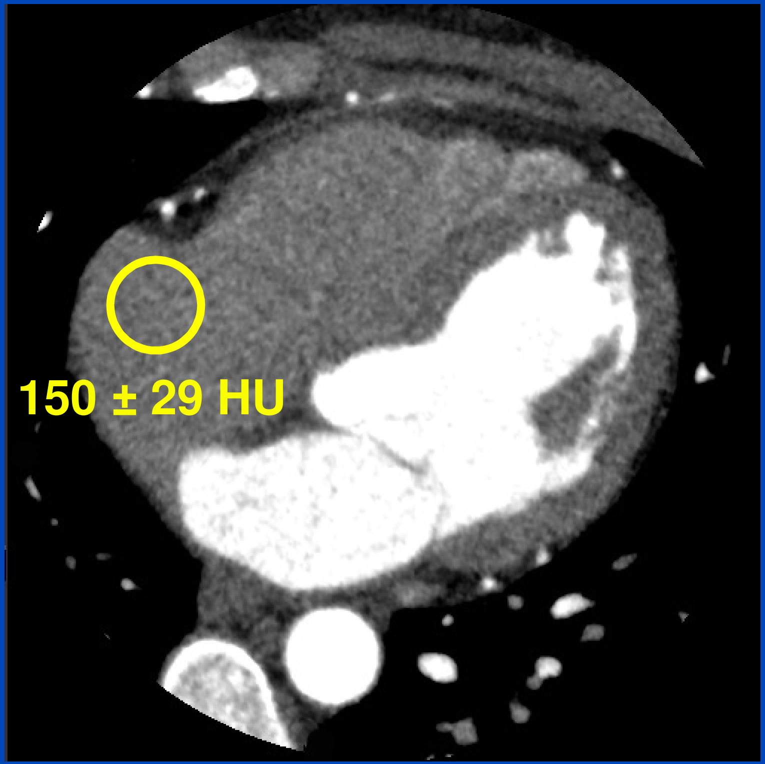


Courtesy of Dr. Thomas Köhler, Philips, Germany.

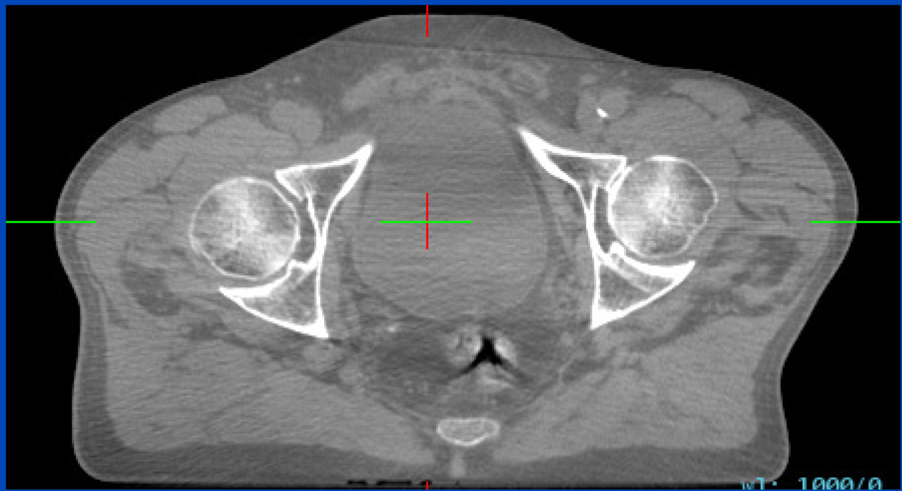
Filtered Backprojection

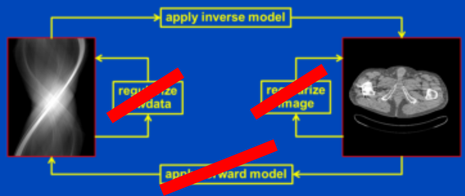


AIDR3D

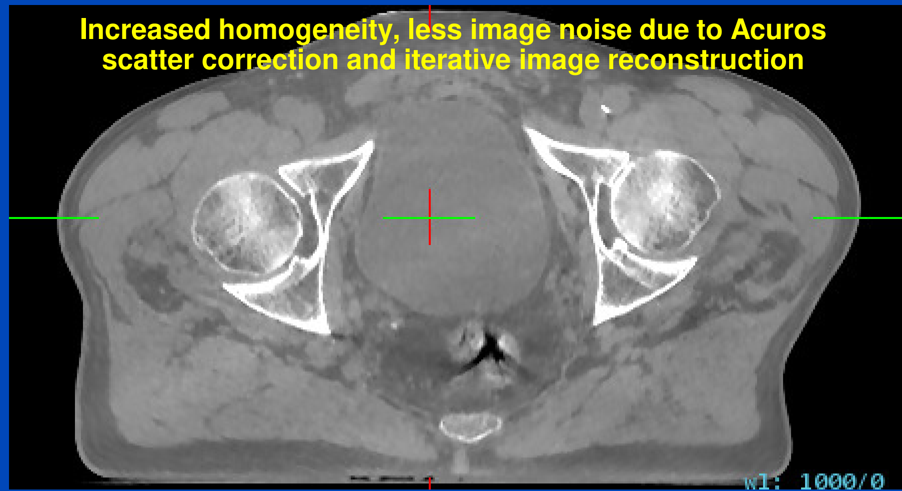


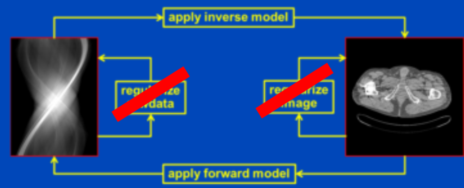
Original CBCT Reconstruction



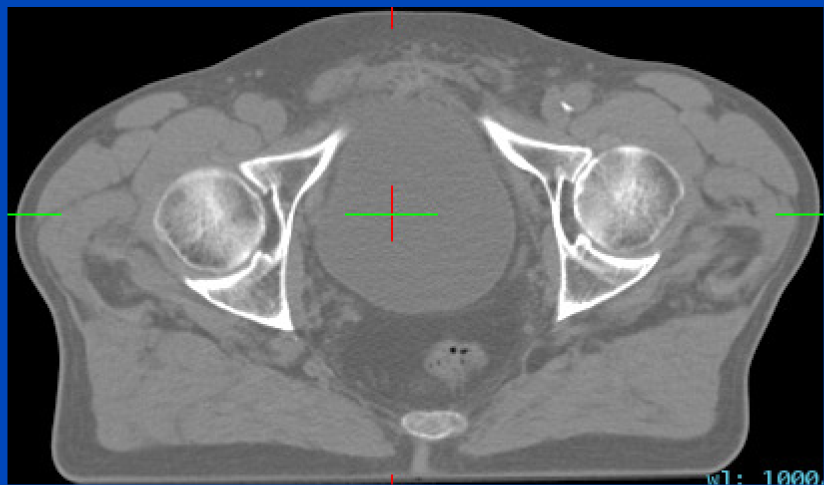


iCBCT Reconstruction



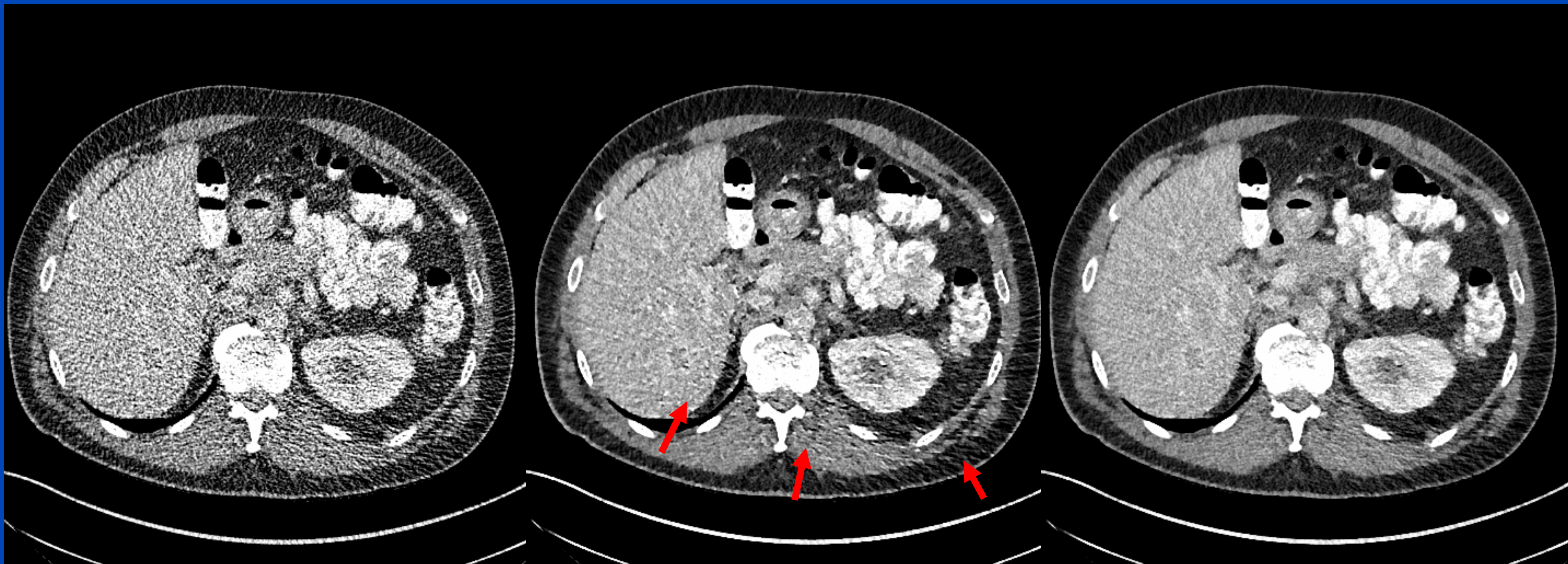


Planning CT for reference



C **= 0 HU,** ***W*** **= 1000 HU**

Vendor's Improvements in Iterative Reconstruction



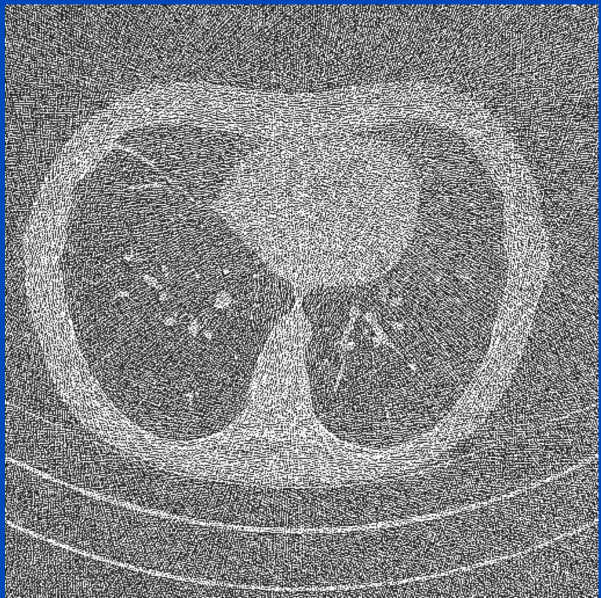
Standard
B40

SAFIRE
I40/5

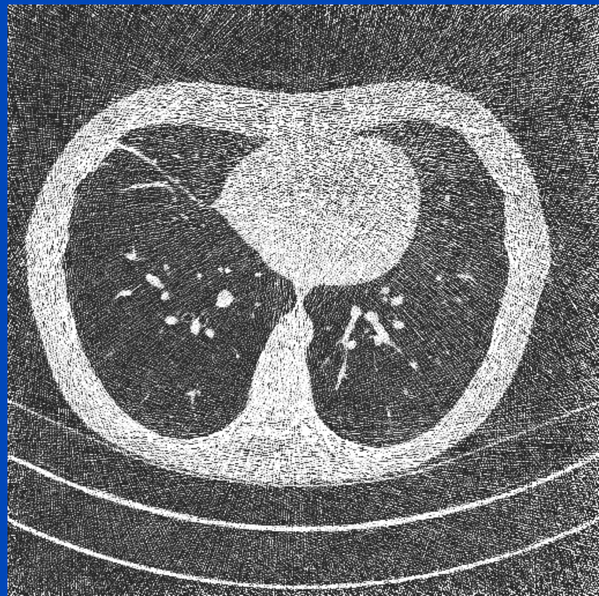
ADMIRE
I40/5

Images provided by Siemens Healthcare, Forchheim, Germany

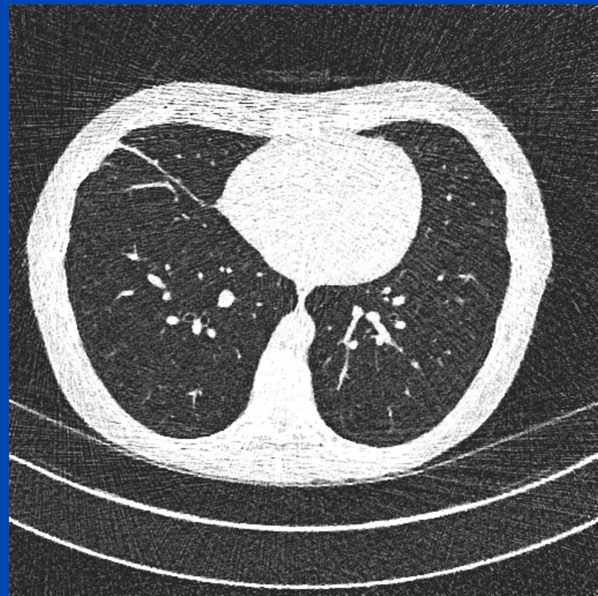
Vendor's Improvements in Iterative Reconstruction



Standard
B64



SAFIRE
I64/5

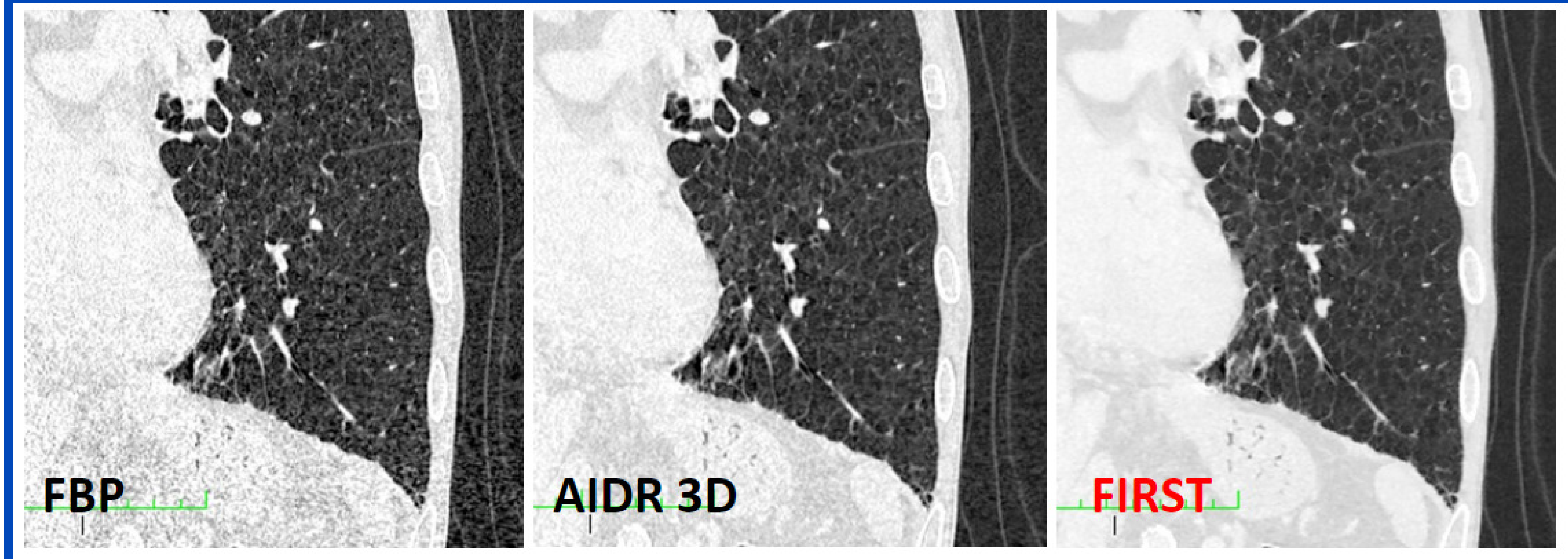


ADMIRE
I64/5

Extremely low dose case: $CTDI_{vol}$ = 0.04 mGy, DLP = 1.64 mGy·cm, D_{eff} = 0.025 mSv

Images provided by Siemens Healthcare, Forchheim, Germany

Vendor's Improvements in Iterative Reconstruction

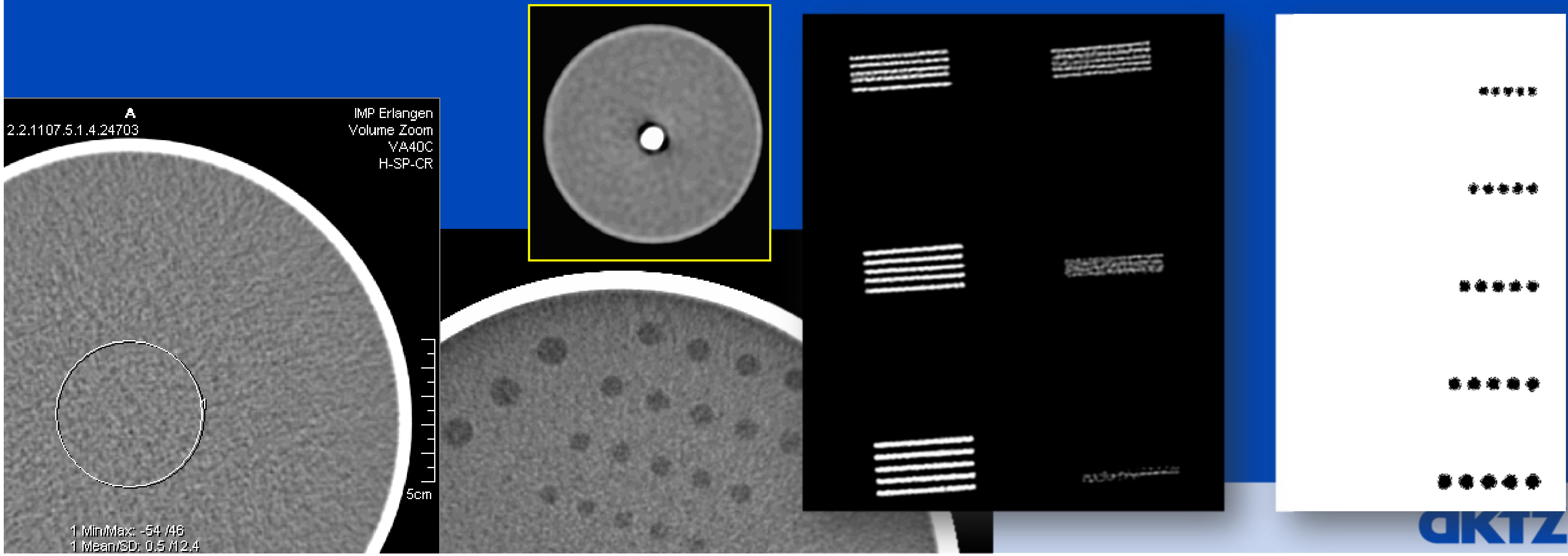


Canon Aquilion ONE ViSION FIRST Edition

Akagi et al. Full Iterative Reconstruction Optimized for Specific Organs - Principle and Capabilities. RSNA 2015.

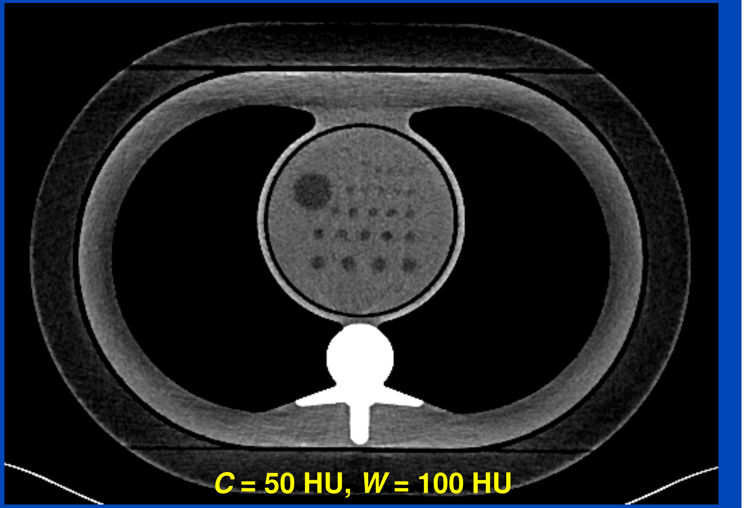
Usual Assumption:
CT is Linear and Translation Invariant

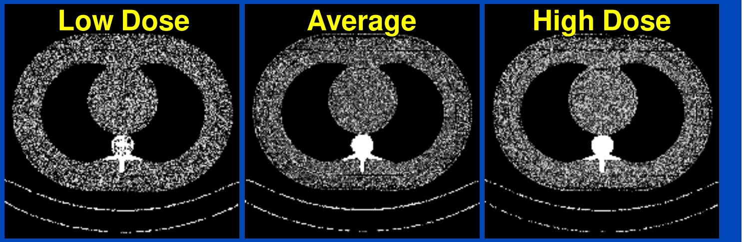
- PSF and MTF are well-defined
- Noise is well-defined
- Noise and spatial resolution are related
- Parameters are valid for all objects
- Simple phantoms can be used to assess image quality
- …



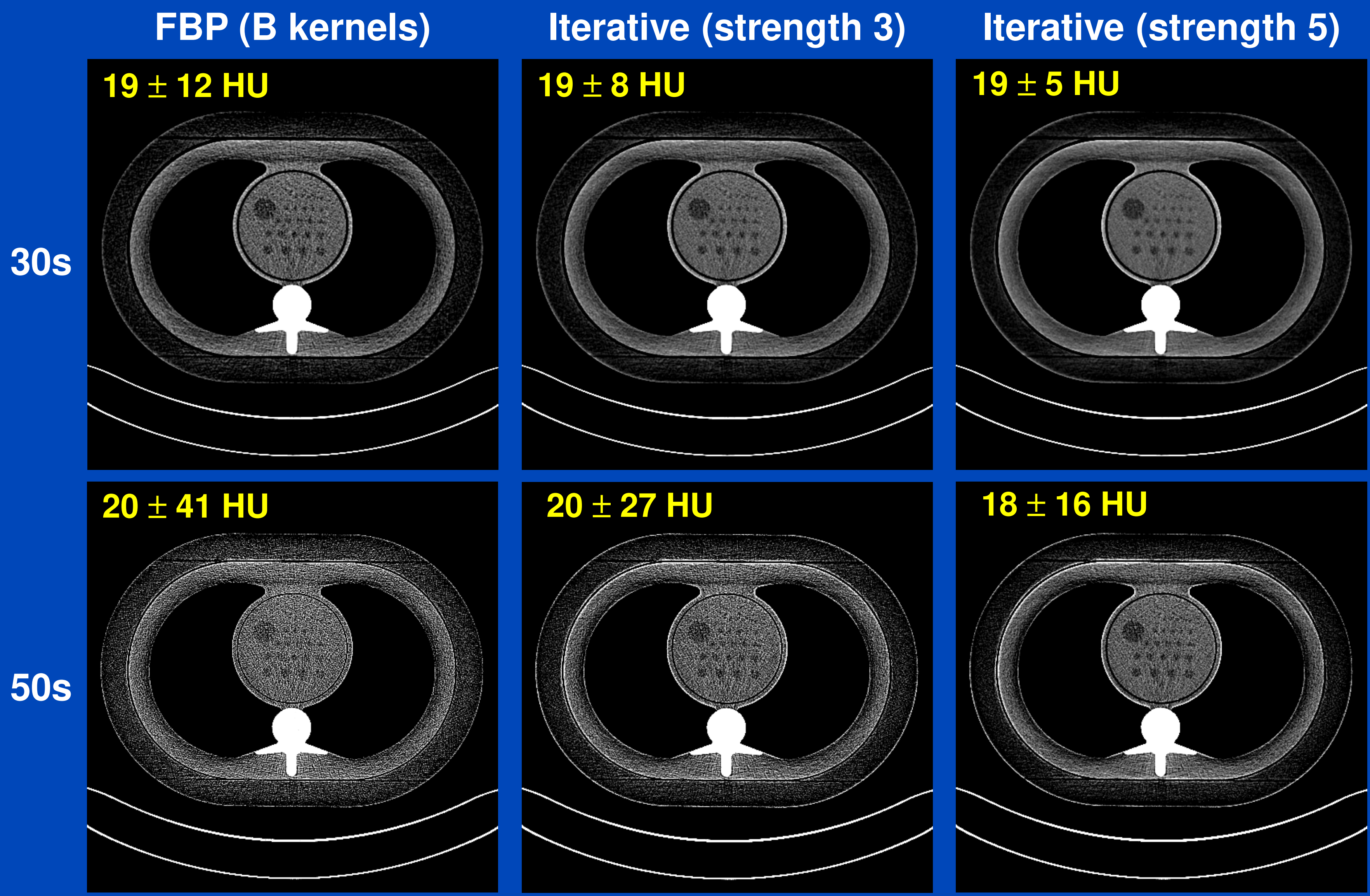
Analysis of Siemens' SAFIRE Algorithm
(Taken at the Siemens Somatom Flash DSCT Scanner)

- Semiantropomorphic phantom
  - 20 cm × 30 cm thorax phantom of 20 cm length with 2.5 cm water extension ring, totalling to 25 cm × 35 cm size
  - 10 cm QRM 3D medium contrast insert with 40 HU background and 20 HU lesions (at 120 kV)
- Scan and recon parameters
  - 2·64 × 0.6 mm collimation
  - U = 120 kV
  - p = 0.6
  - t_{rot} = 1.0 s
  - S_{eff} = 0.6 mm
  - 1 high dose scan with 1100 mAs_{eff}
  - 25 low dose scans with 44 mAs_{eff} each
  - FBP (= analytical): B30s, B50s
  - SAFIRE (= iterative): I30s and I50s, strengths 3 and 5
  - Averaging of 25 low dose scans after reconstruction
  - Mean±StdDev in large medium contrast lesion
  - Display at C = 50 HU and W = 100 HU





Average of 25 Low Dose Scans

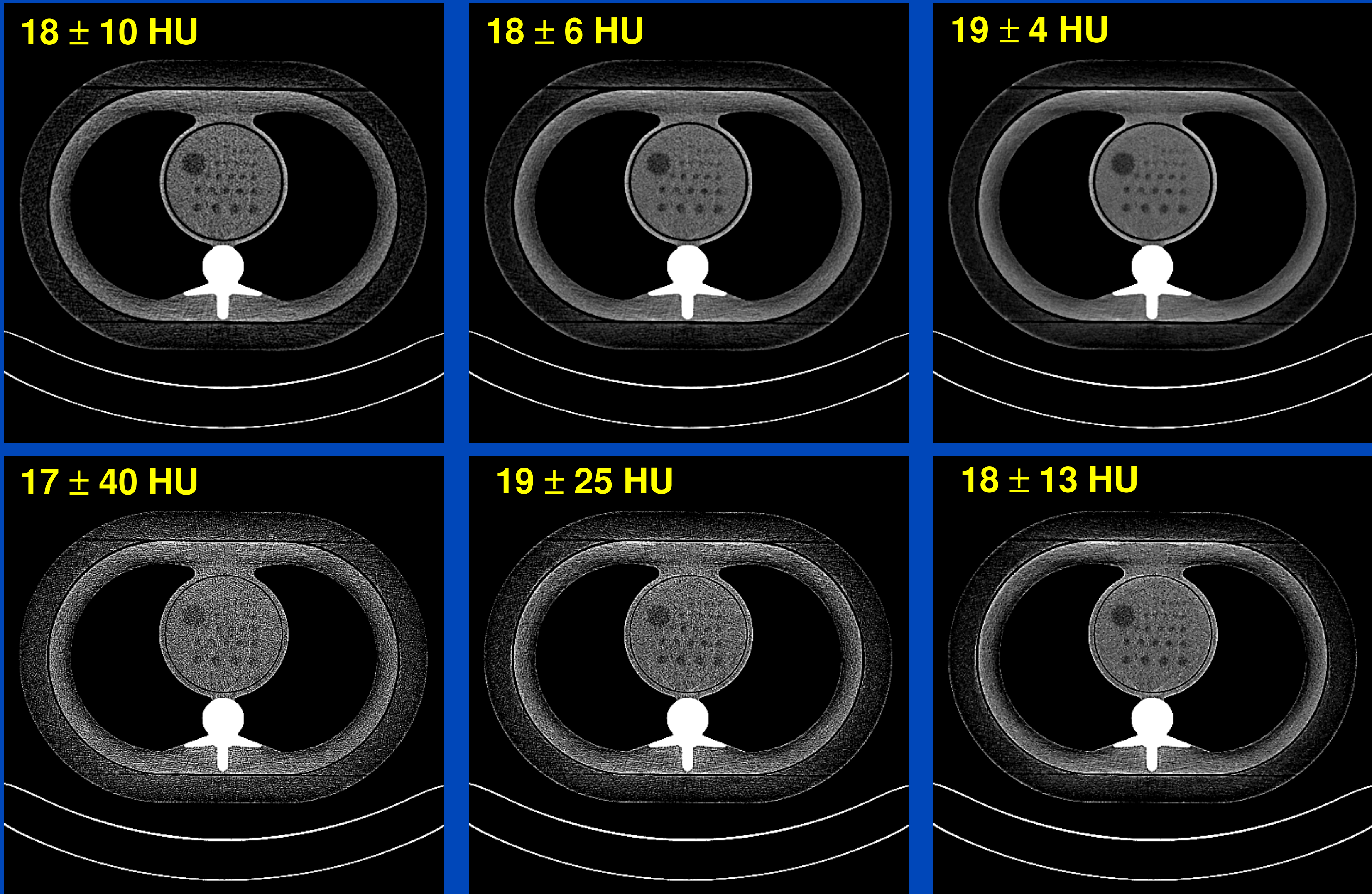


High Dose Scan

FBP (B kernels) | Iterative (strength 3) | Iterative (strength 5)

30s

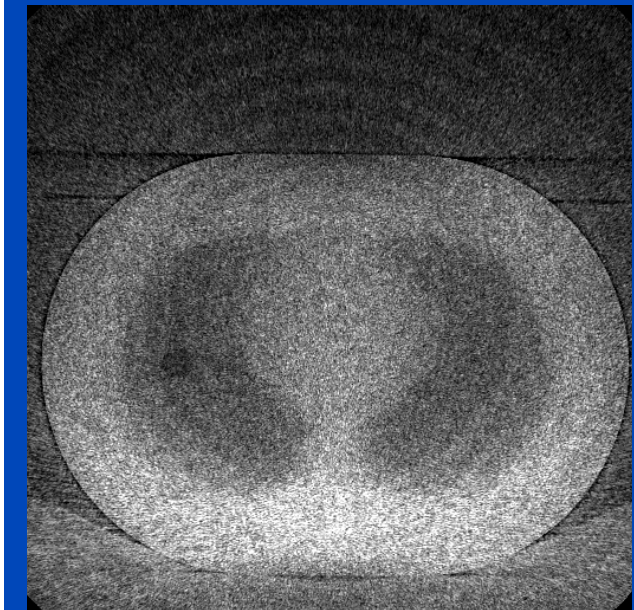
50s



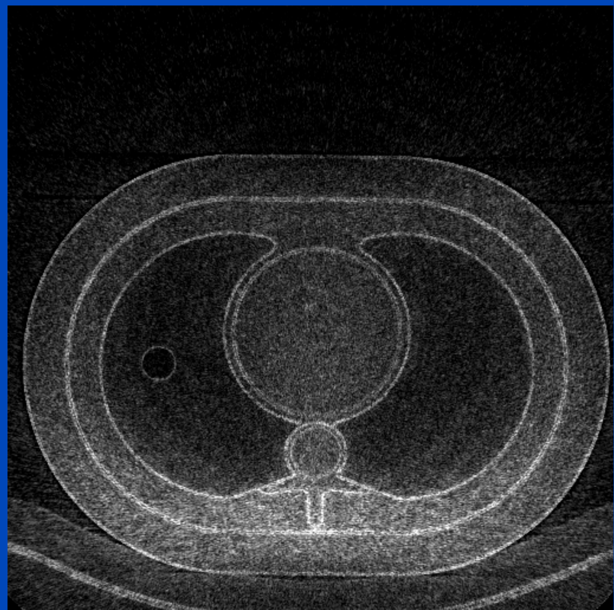
Noise Evaluation using Sigma Images

- **Same phantom as in example 1**
- **Same scans as in example 1**
- **Calculation of sigma images from the 25 independent samples**
  - **Compute unbiased estimator for the sample variance for each pixel**
  - **Take the square-root of each pixel's estimated variance**

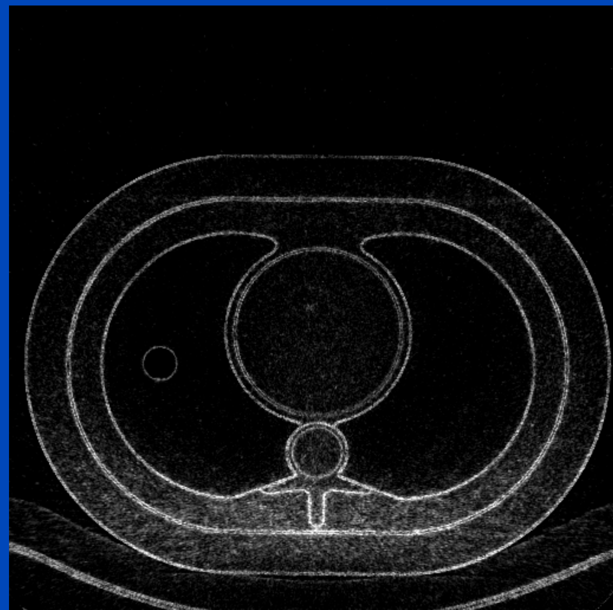
FBP (B30s)



SAFIRE (I30s strength 3)



SAFIRE (I30s strength 5)



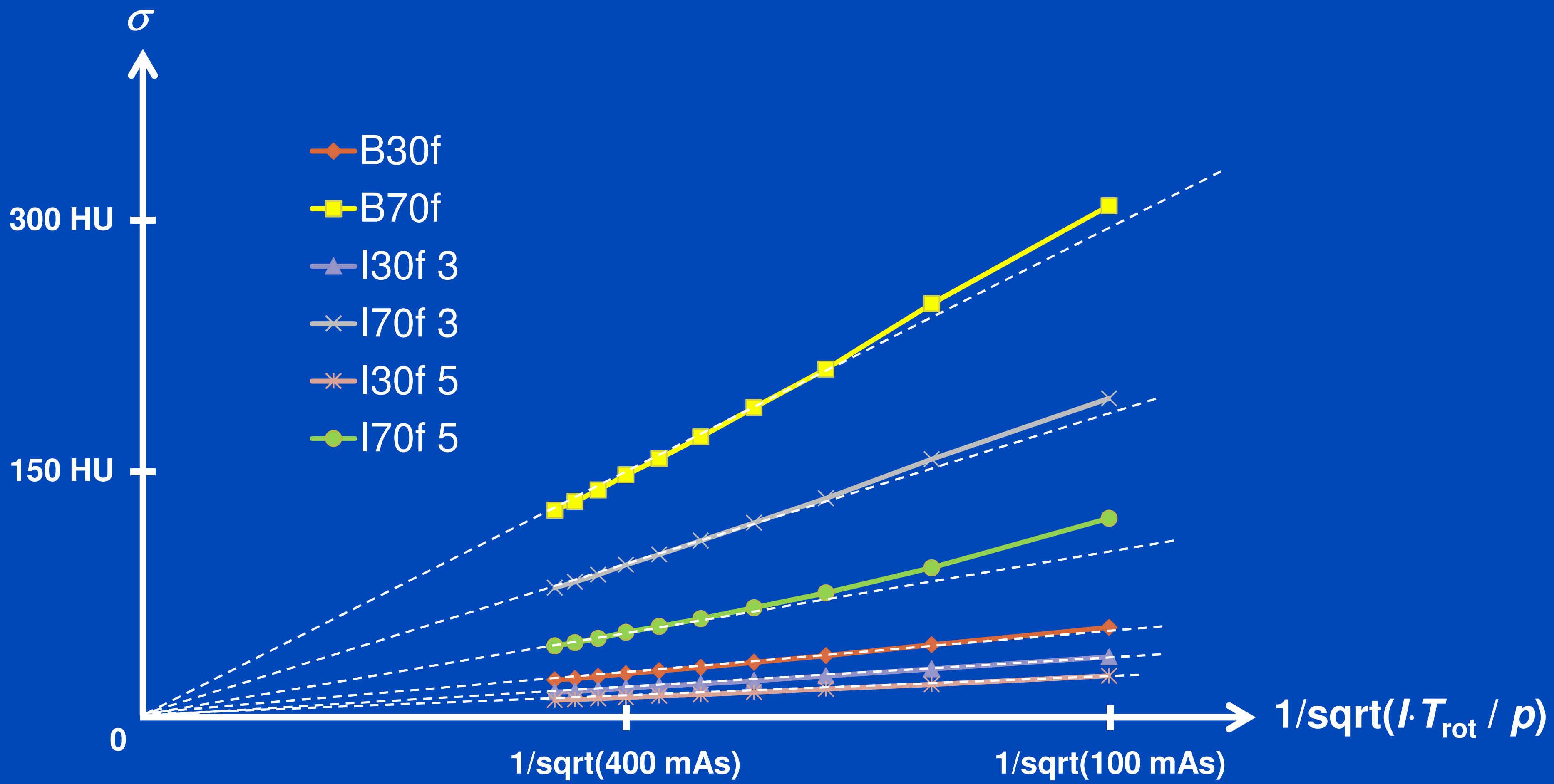
C = 40 HU, W = 50 HU

Noise vs. mAs_{eff}

(Taken at the Siemens Somatom Flash DSCT Scanner)

- Abdomen phantom + small fat ring
- Tube voltage U = 120 kV
- Slice thickness S_{eff} = 0.6 mm
- Pitch p = 0.6
- Variation of the effective tube current
  - mAs_{eff} = 100 mAs … 550 mAs
  - DLP = 57 … 312 mGy·cm
- Noise was measured in VOIs

Image Noise vs. mAs_{eff}



dkfz.

Analysis of GE‘s MBIR (Veo) Iterative Reconstruction Algorithm

Statistical model based iterative reconstruction (MBIR) in clinical CT systems. Part II. Experimental assessment of spatial resolution performance

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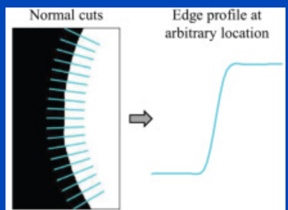
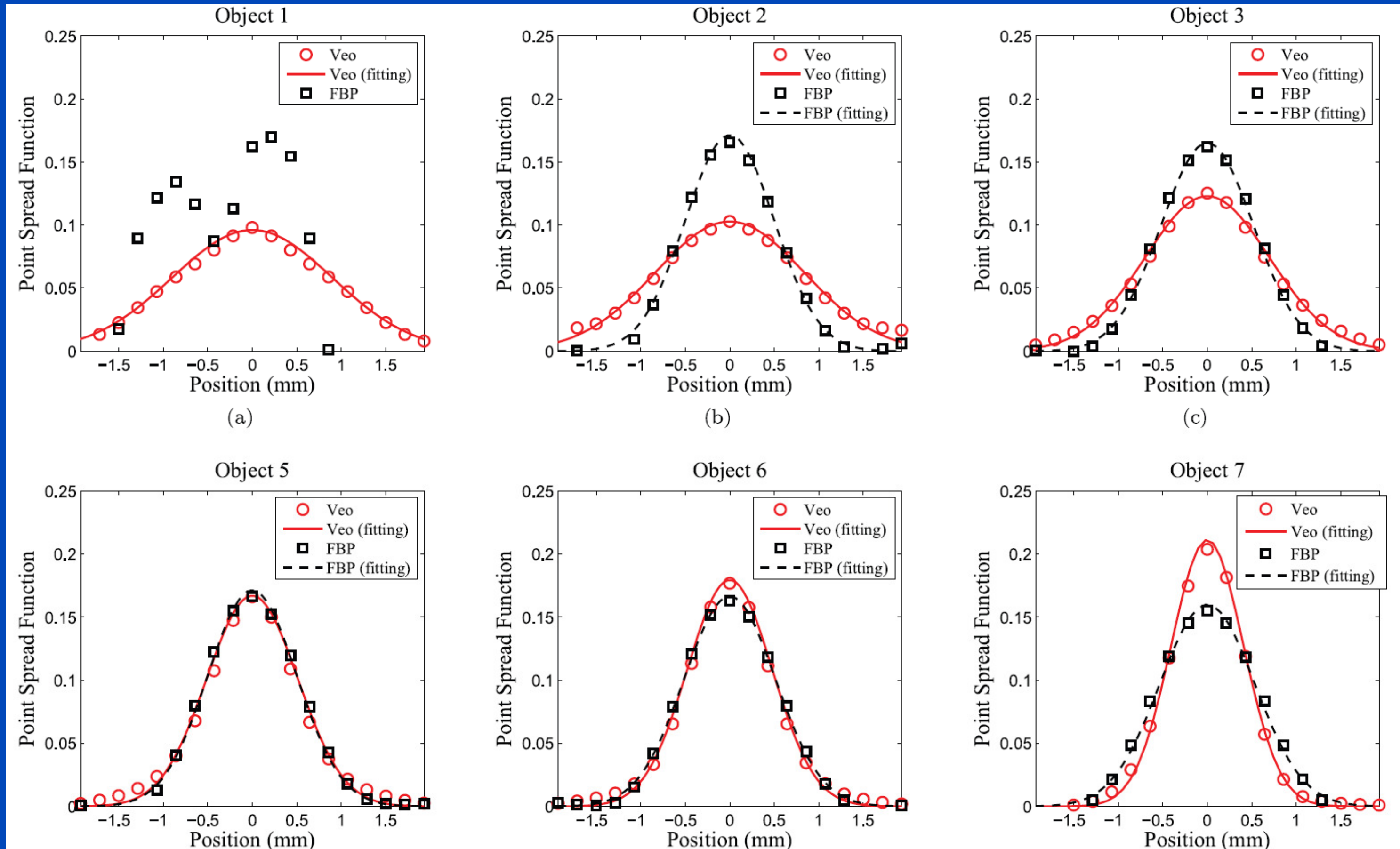
Contrast Dependency of the PSF
(of GE's FBP and Veo Algorithms)

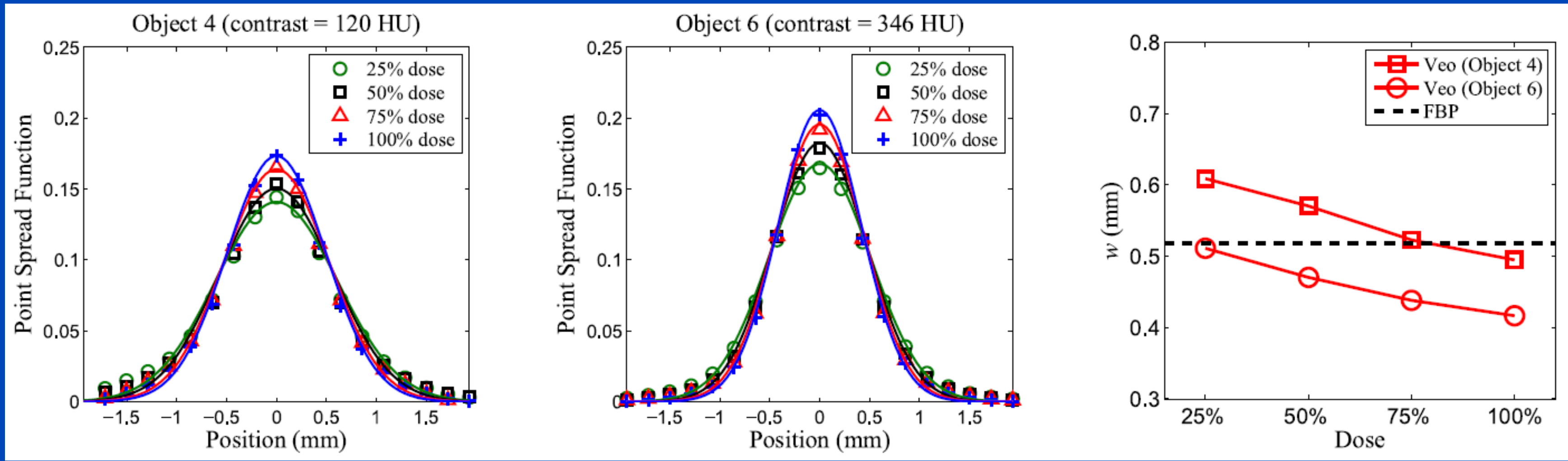
	Contrast (HU)
Object 1	13
Object 2	33
Object 3	62
Object 4	120
Object 5	224
Object 6	346
Object 7	814
Object 8	1710





Li et al., MedPhys 41(7), July 2014

Dose Dependency of the PSF
(of GE's FBP and Veo Algorithms)

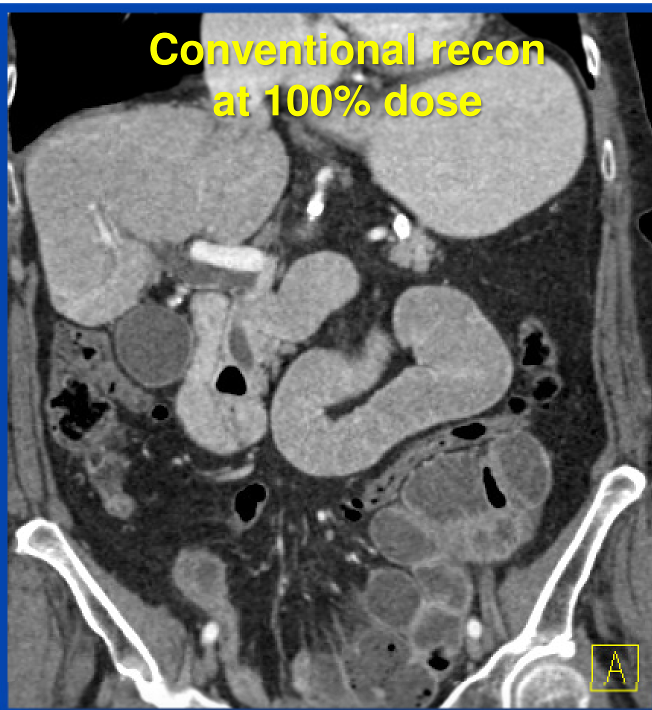


Conclusions on Li et al. (Veo Algorithm)

- Our previous findings (from the simple examples) are confirmed.
- Spatial resolution is a function of
  - location
  - contrast
  - dose
  - ...

Summary

- Analytical image reconstruction
  - is compute efficient
  - requires new solutions for new trajectories
  - is what most images are reconstructed with
- Iterative image reconstruction
  - requires much more computational effort
  - allows to easily model constraints
  - allows to incorporate prior knowledge
- Practical modern solutions
  - often are a combination of analytical and iterative recon
  - are offered by the major manufacturers of diagnostic CT
- Future
  - Let neural networks do the regularization



Images provided by Siemens Healthcare, Forchheim, Germany

Thank You!

The 6th International Conference on
Image Formation in X-Ray Computed Tomography

Conference Chair: **Marc Kachelrieß**, German Cancer Research Center (DKFZ), Heidelberg, Germany

This presentation will soon be available at www.dkfz.de/ct.
Job opportunities through DKFZ's international Fellowship programs (marc.kachelriess@dkfz.de).
Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.