Basics of X-Ray-Based Tomographic Imaging for IGRT 2: CT Image Reconstruction

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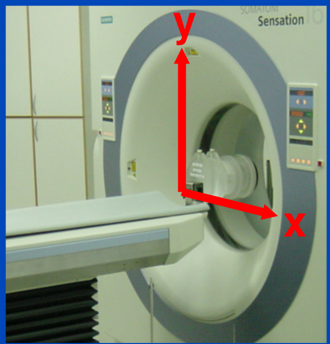
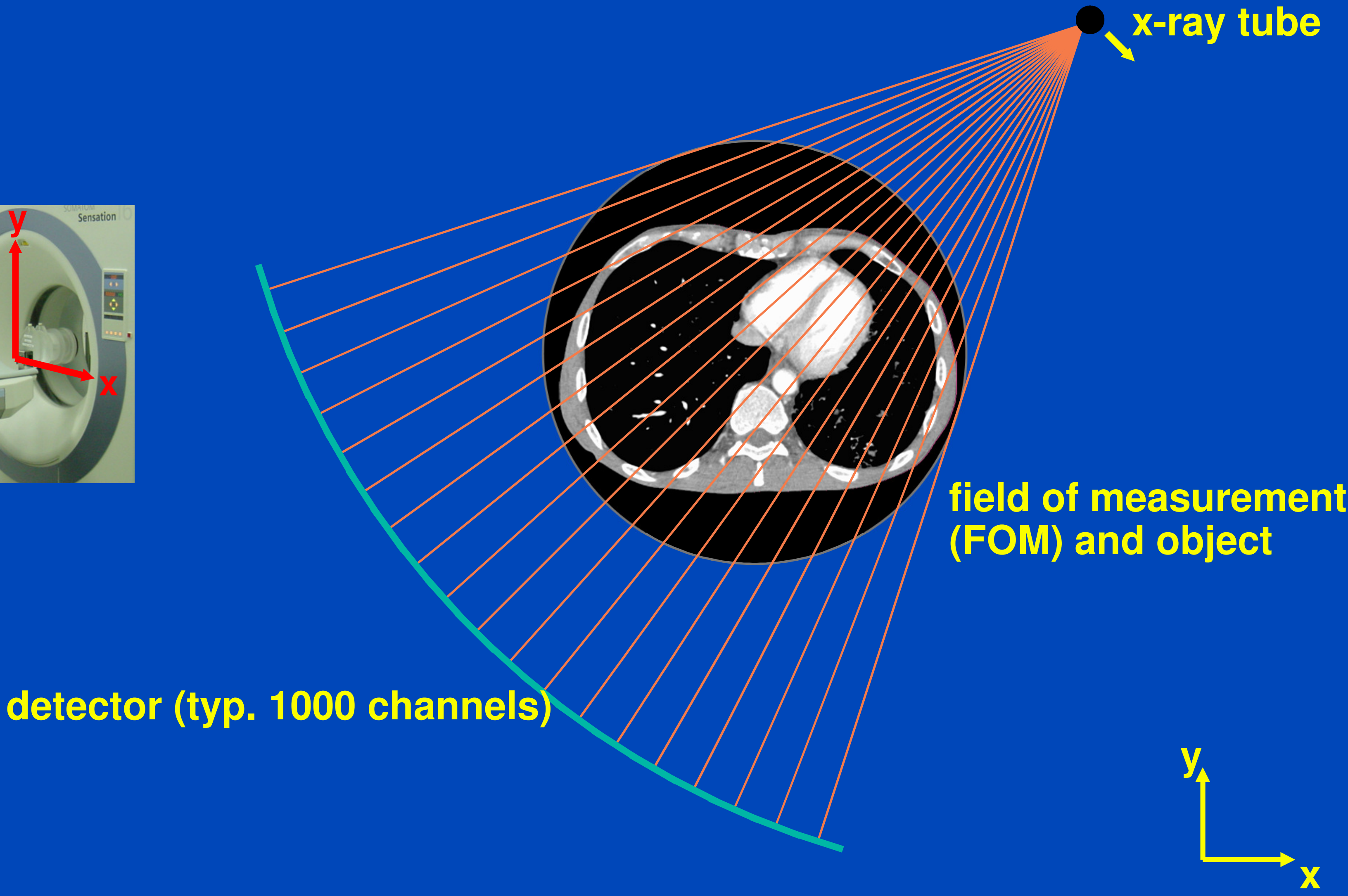
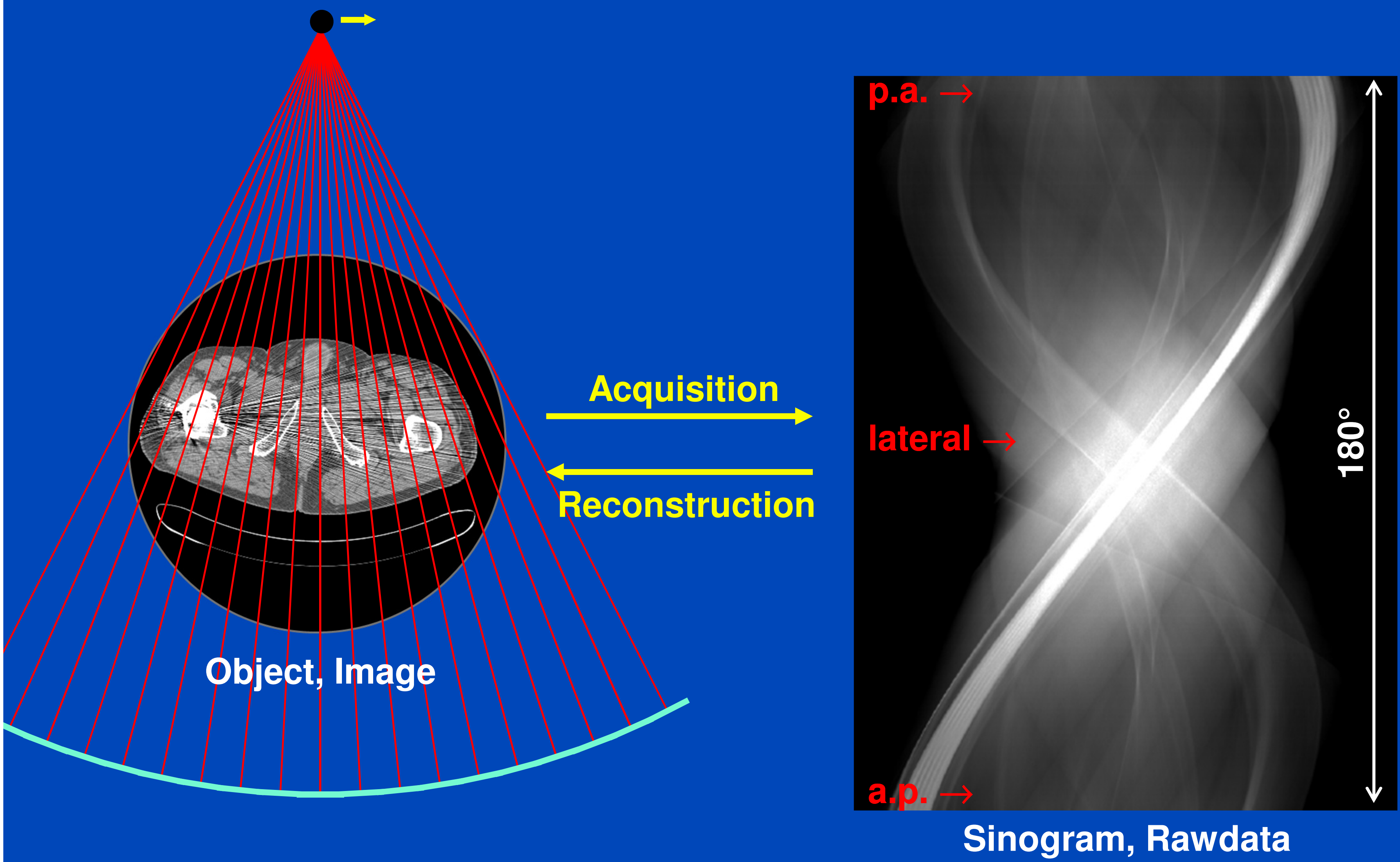
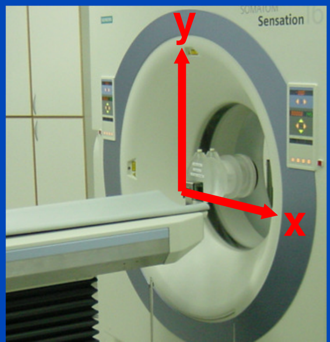
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

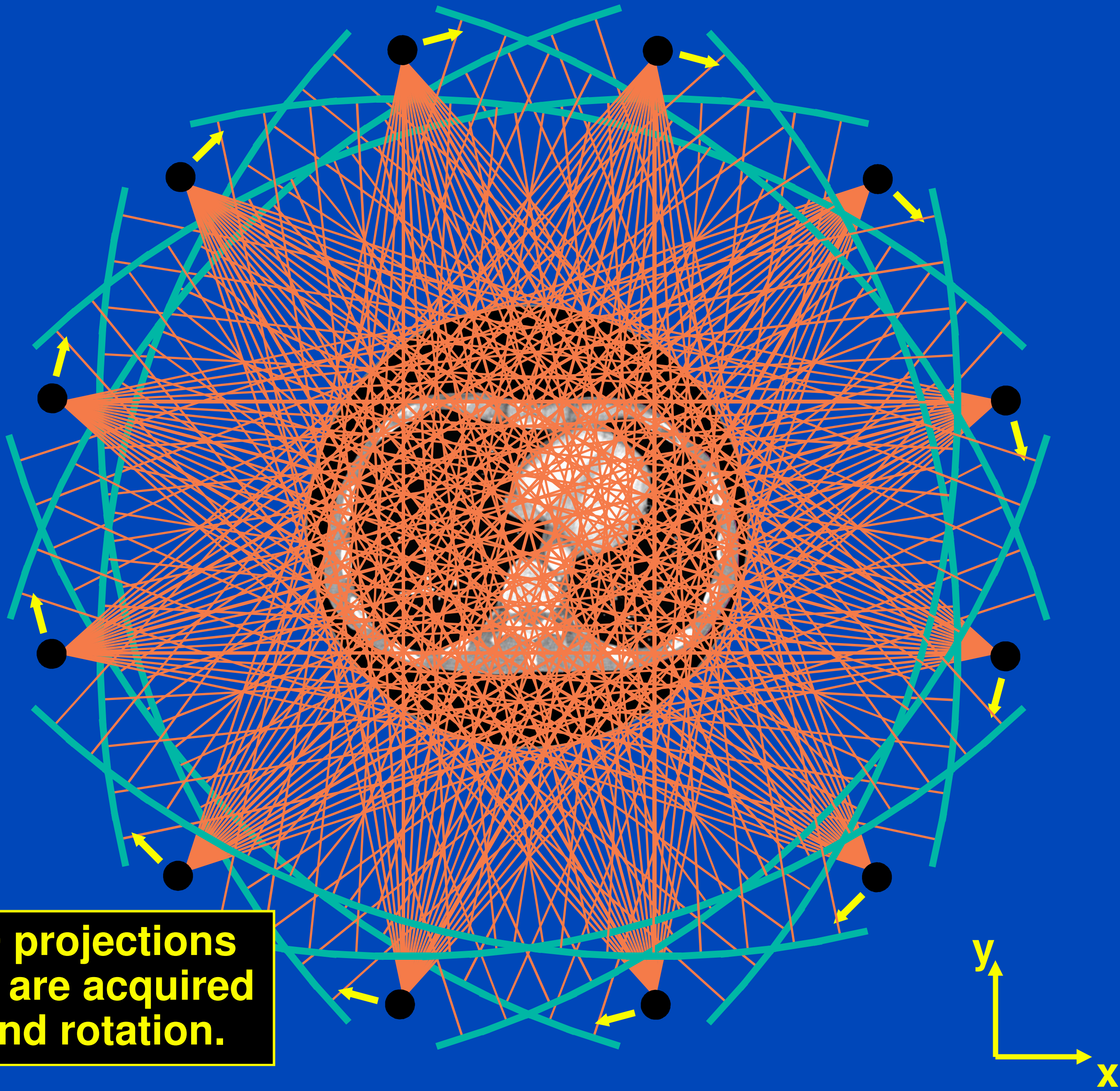
Fan-Beam Geometry
(transaxial / in-plane / x-y-plane)





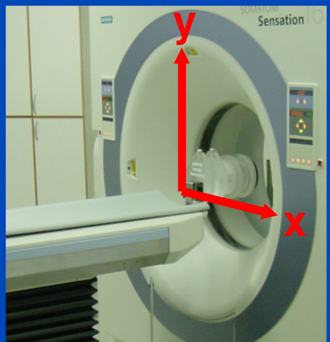

Acquisition
Reconstruction
Object, Image
p.a. →
lateral →
a.p. →
180°
Sinogram, Rawdata

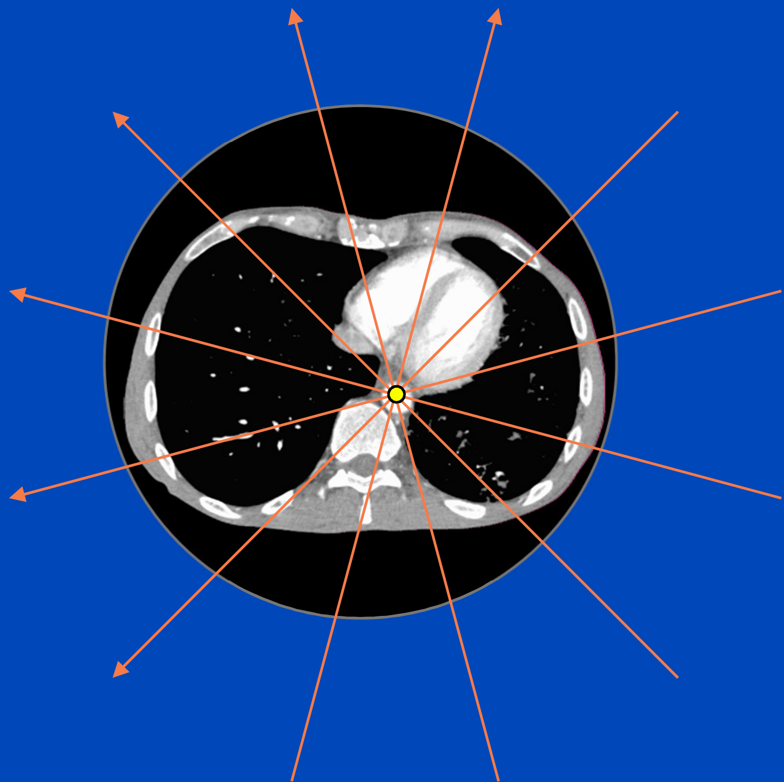




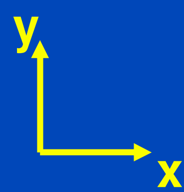
In the order of 1000 projections with 1000 channels are acquired per detector slice and rotation.

Data Completeness

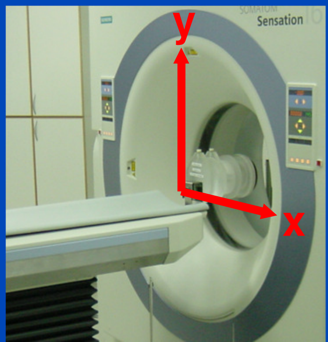


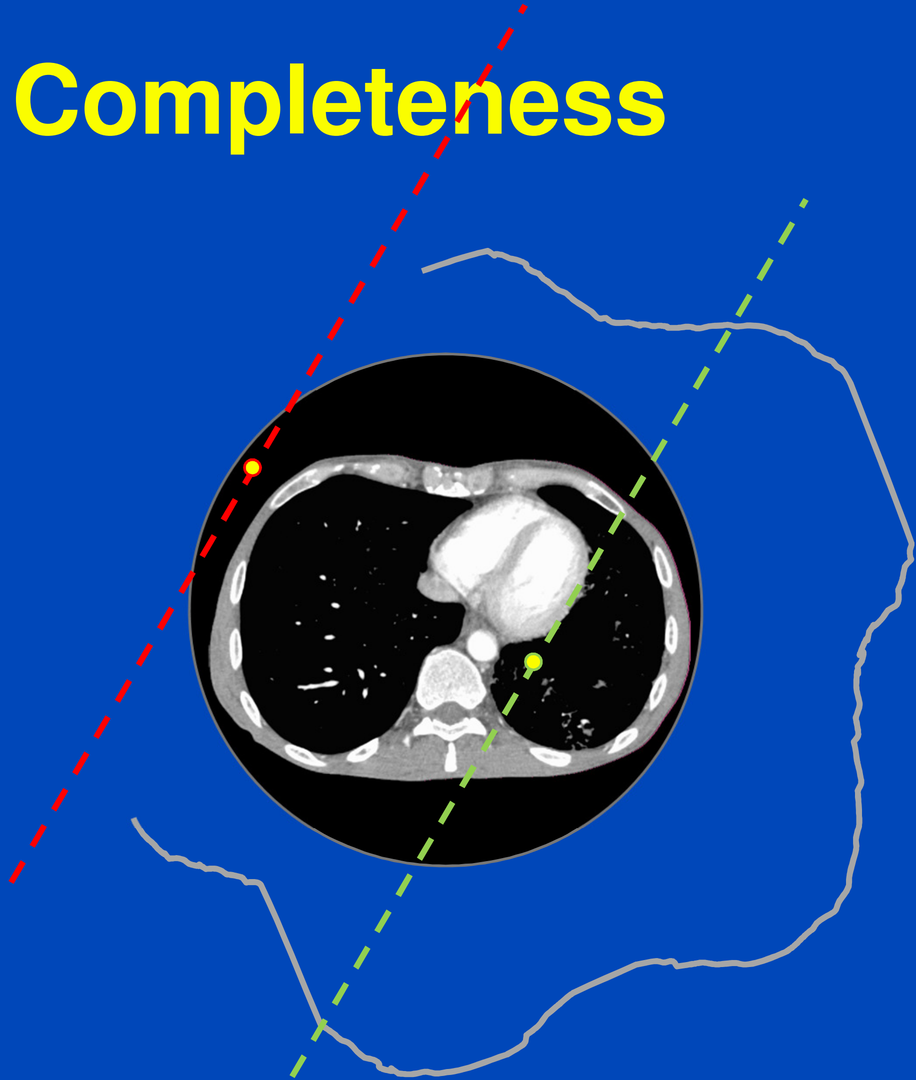


Each object point must be viewed by an angular interval of 180° or more. Otherwise image reconstruction is not possible.

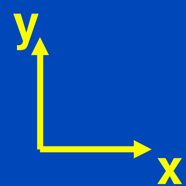


Data Completeness





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

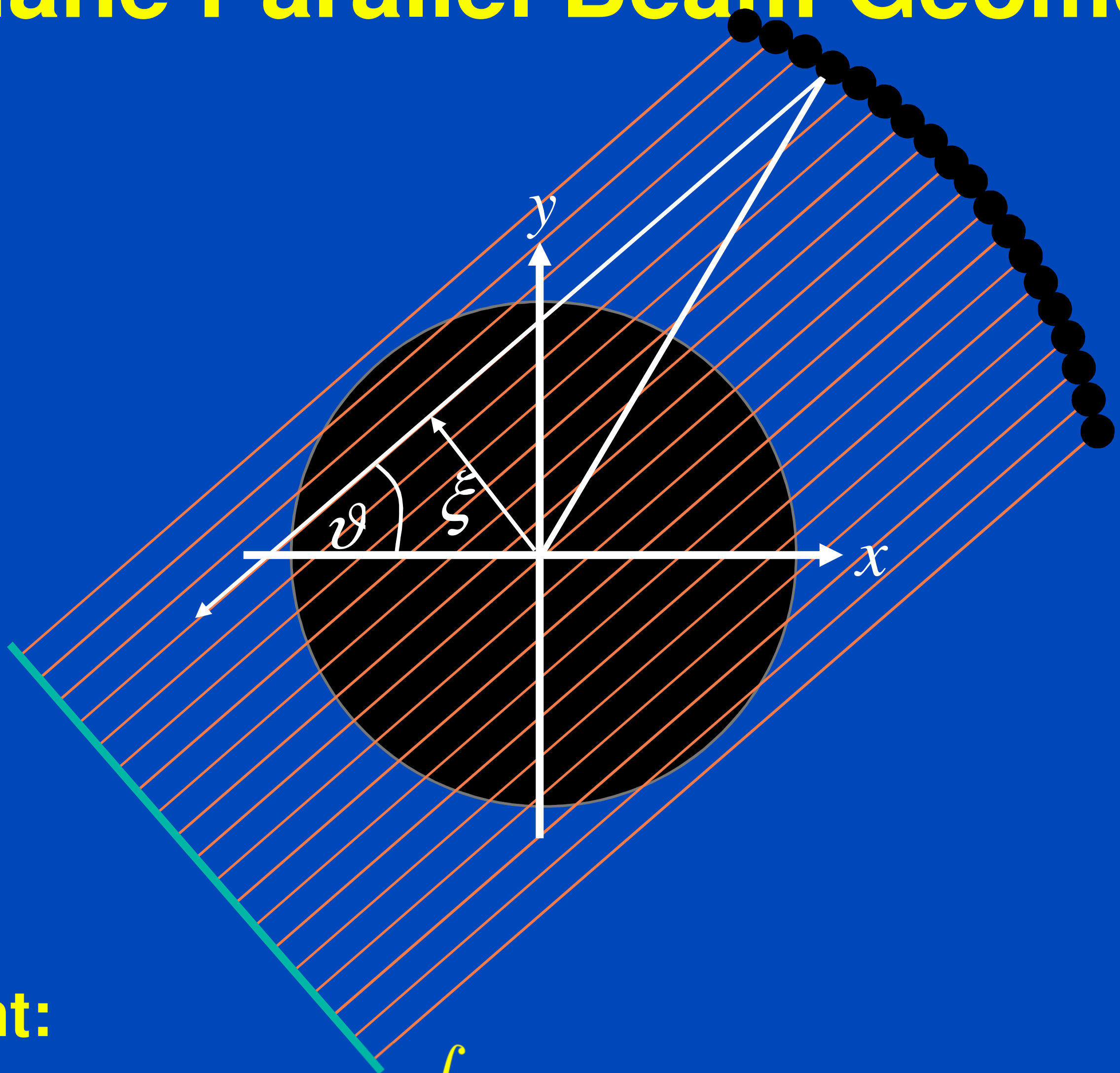
$$x^2 = y$$

Model

$$x = \sqrt{y}$$

Solution

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

Fourier transform:

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

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

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

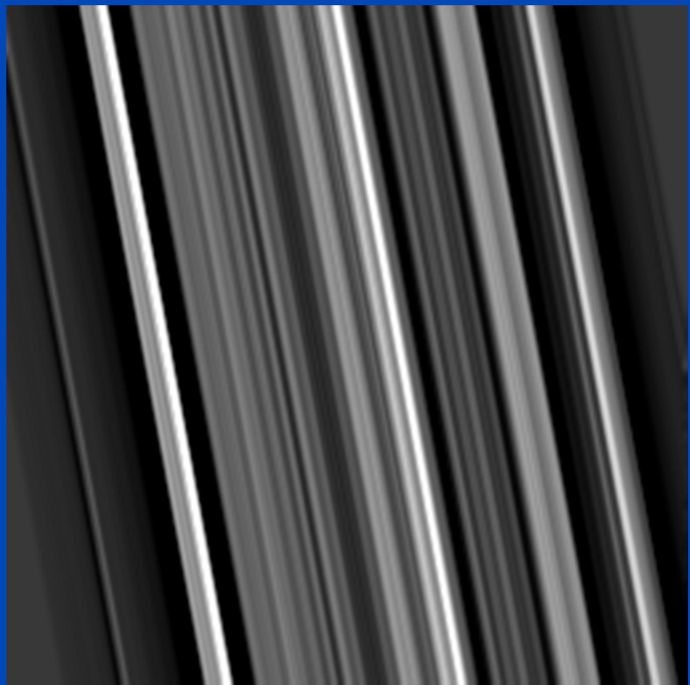
Important: *K*(0) = 0 and *K*´(0±) = ±1

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

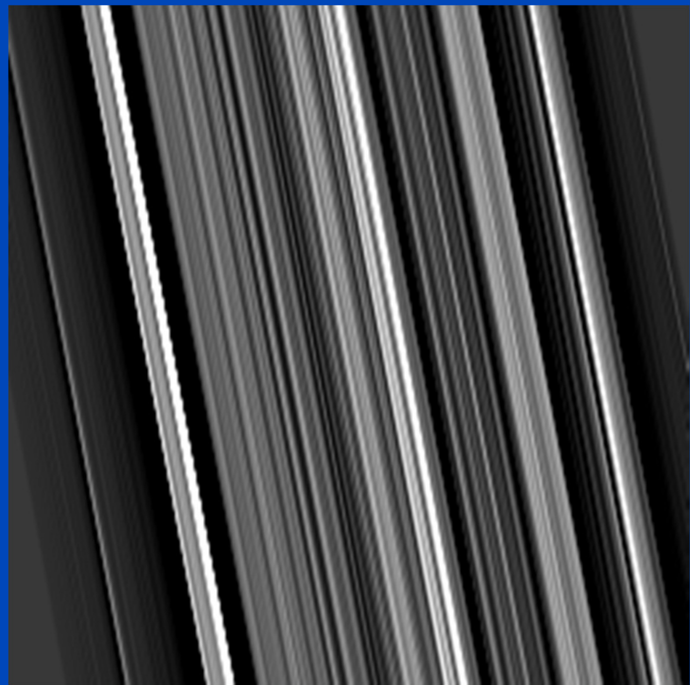
dkfz.

Filtered Backprojection (FBP)

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

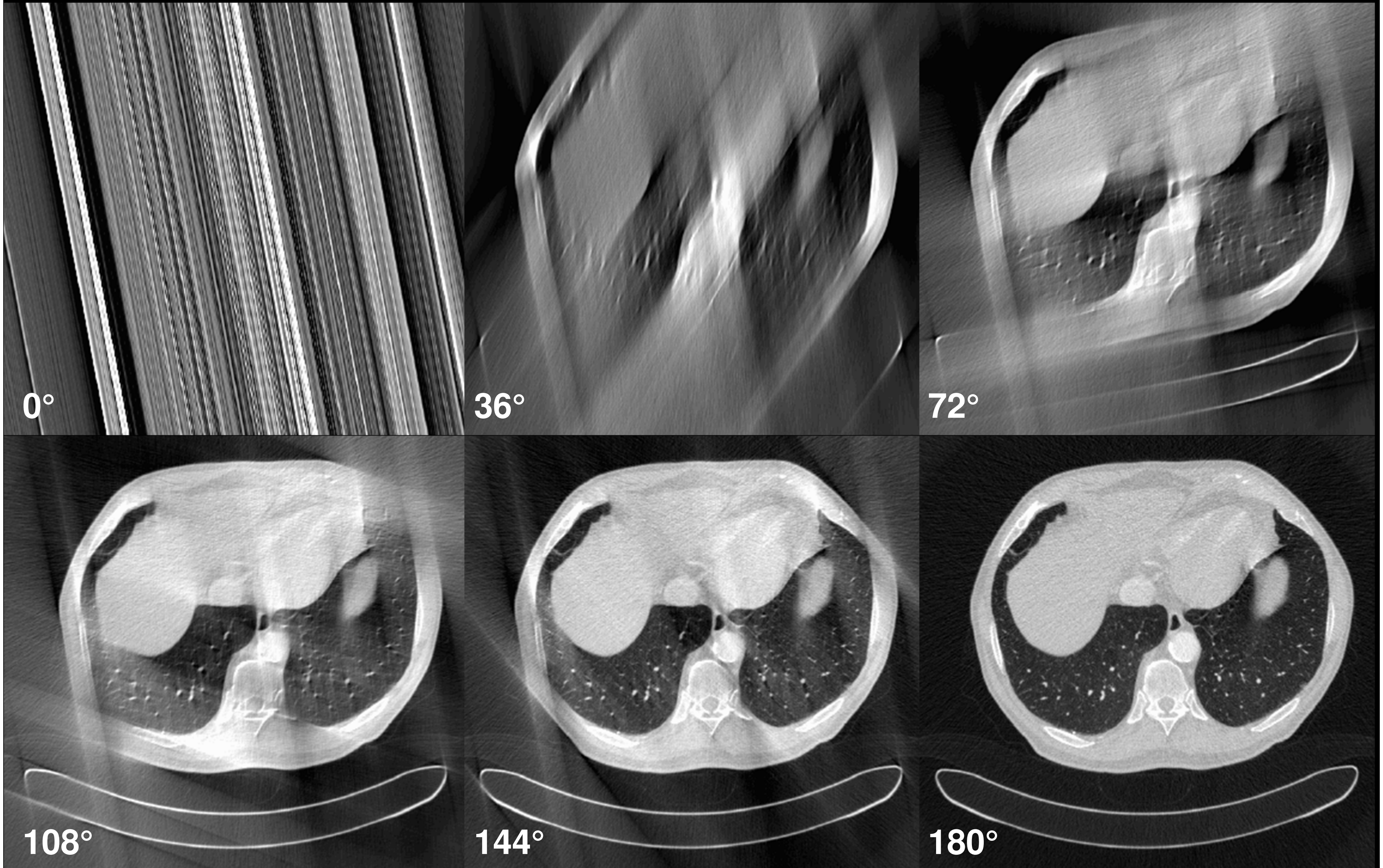


Smooth

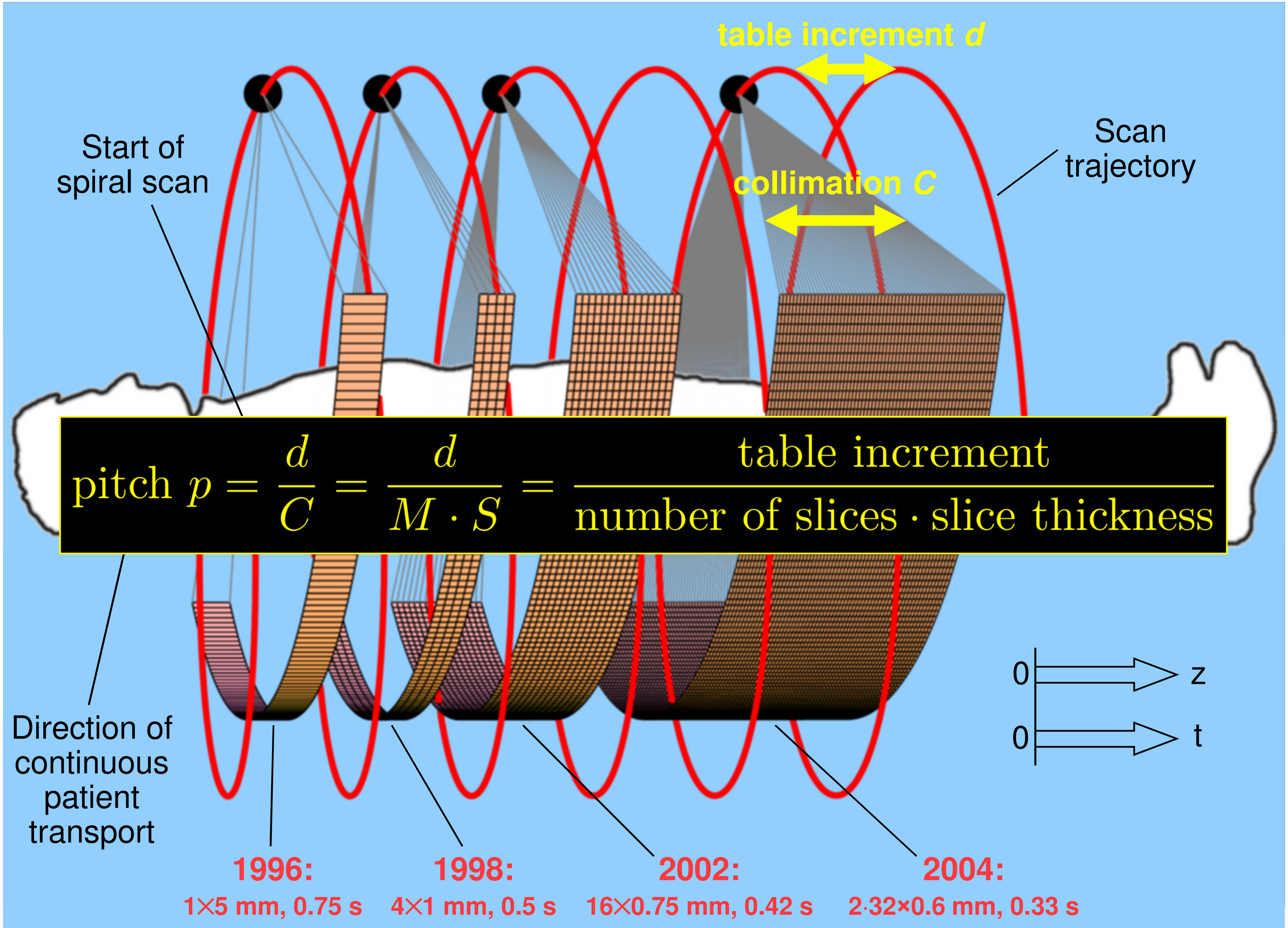


Standard

Reconstruction kernels balance between spatial resolution and image noise.



dkfz.

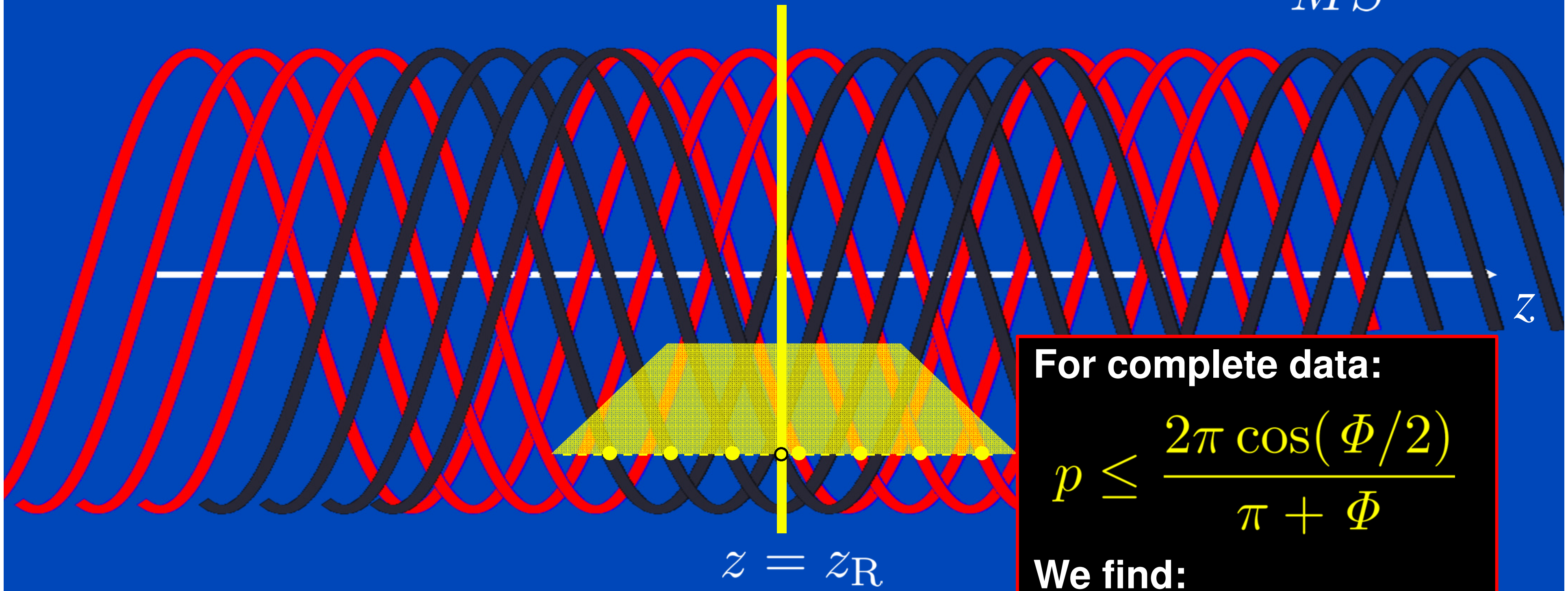


$$\text{pitch } p = \frac{d}{C} = \frac{d}{M \cdot S} = \frac{\text{table increment}}{\text{number of slices} \cdot \text{slice thickness}}$$

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

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

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

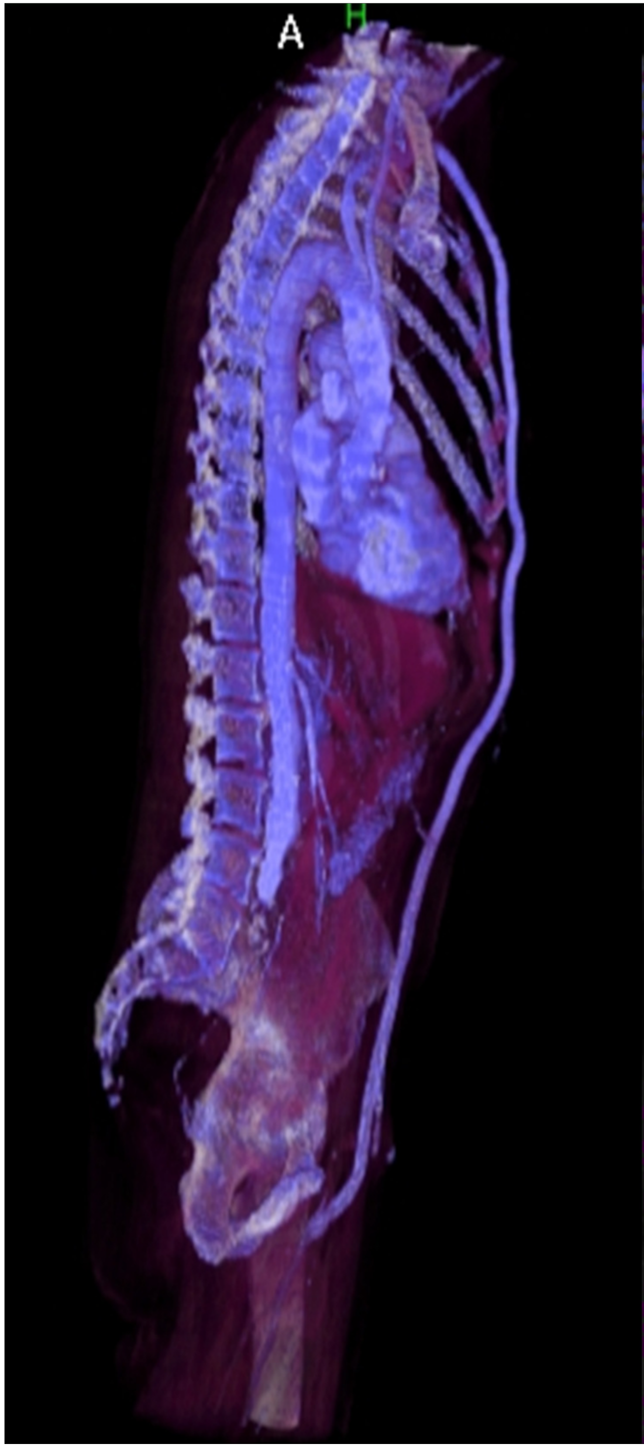


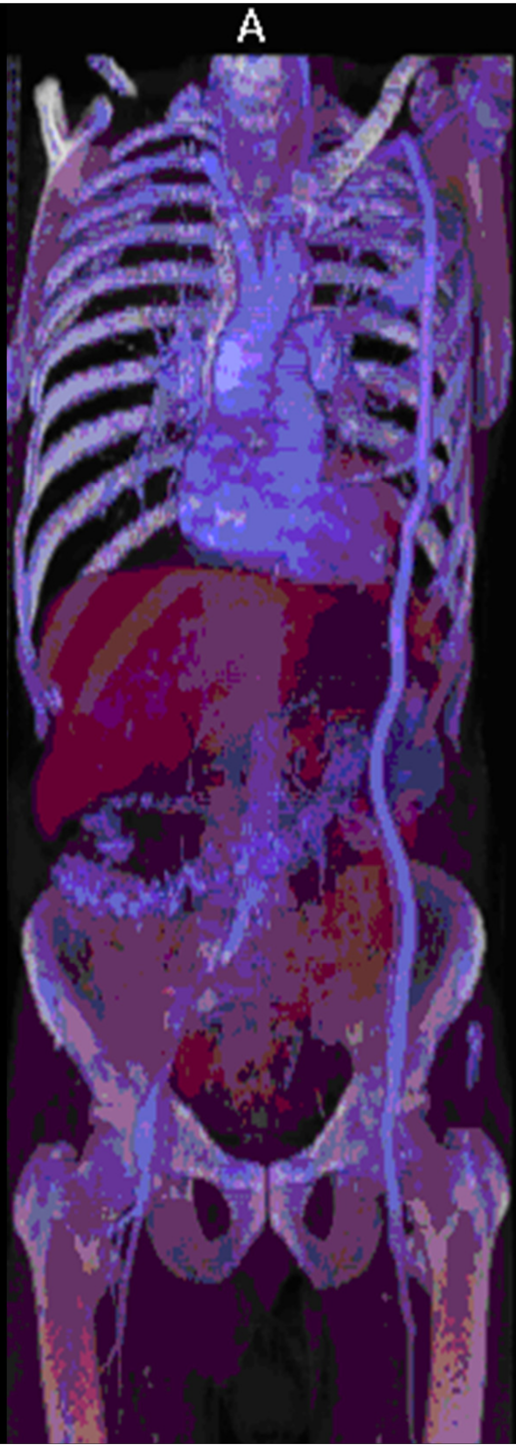
For complete data:

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

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

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



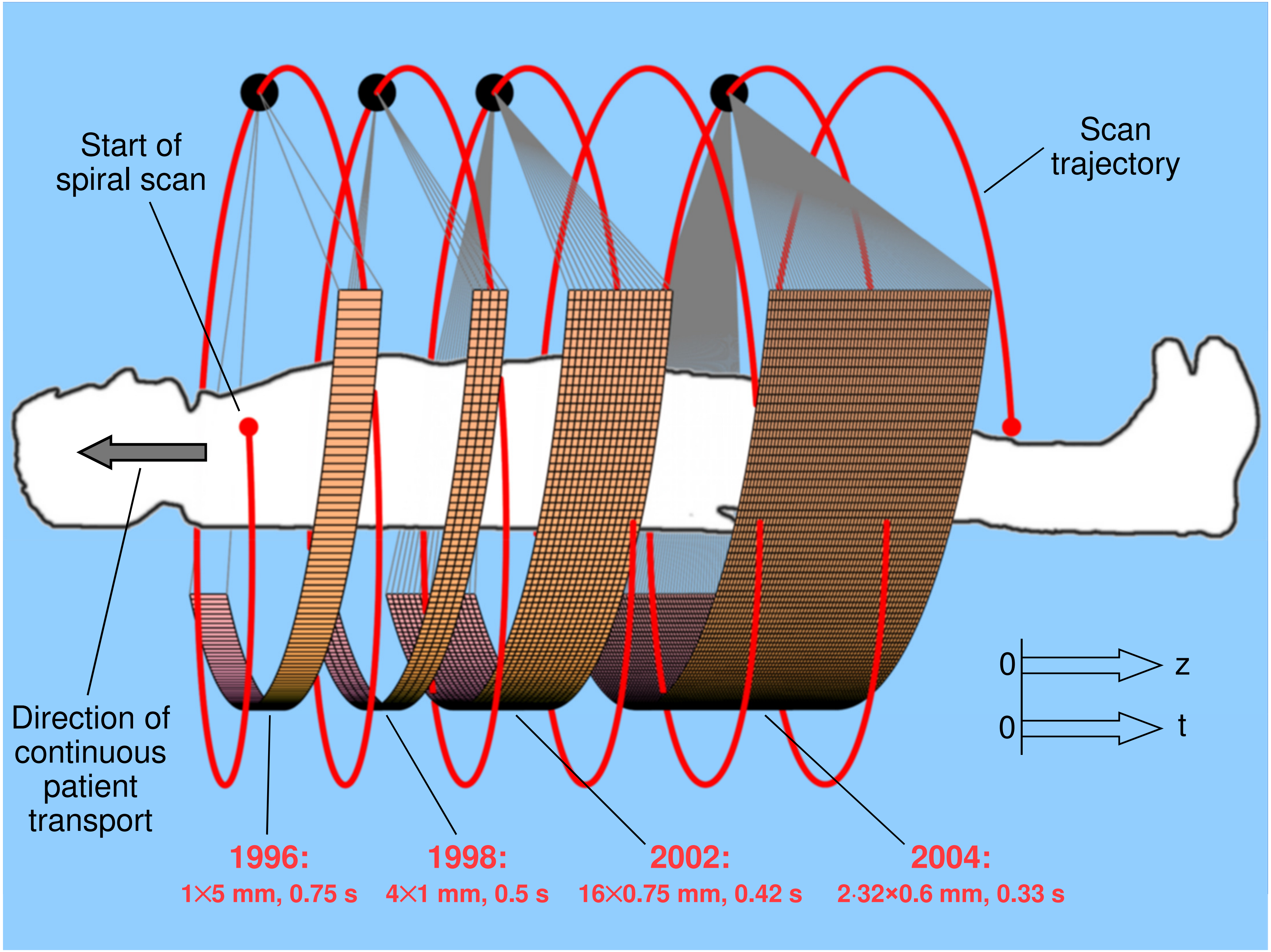


CT Angiography: Axillo-femoral bypass

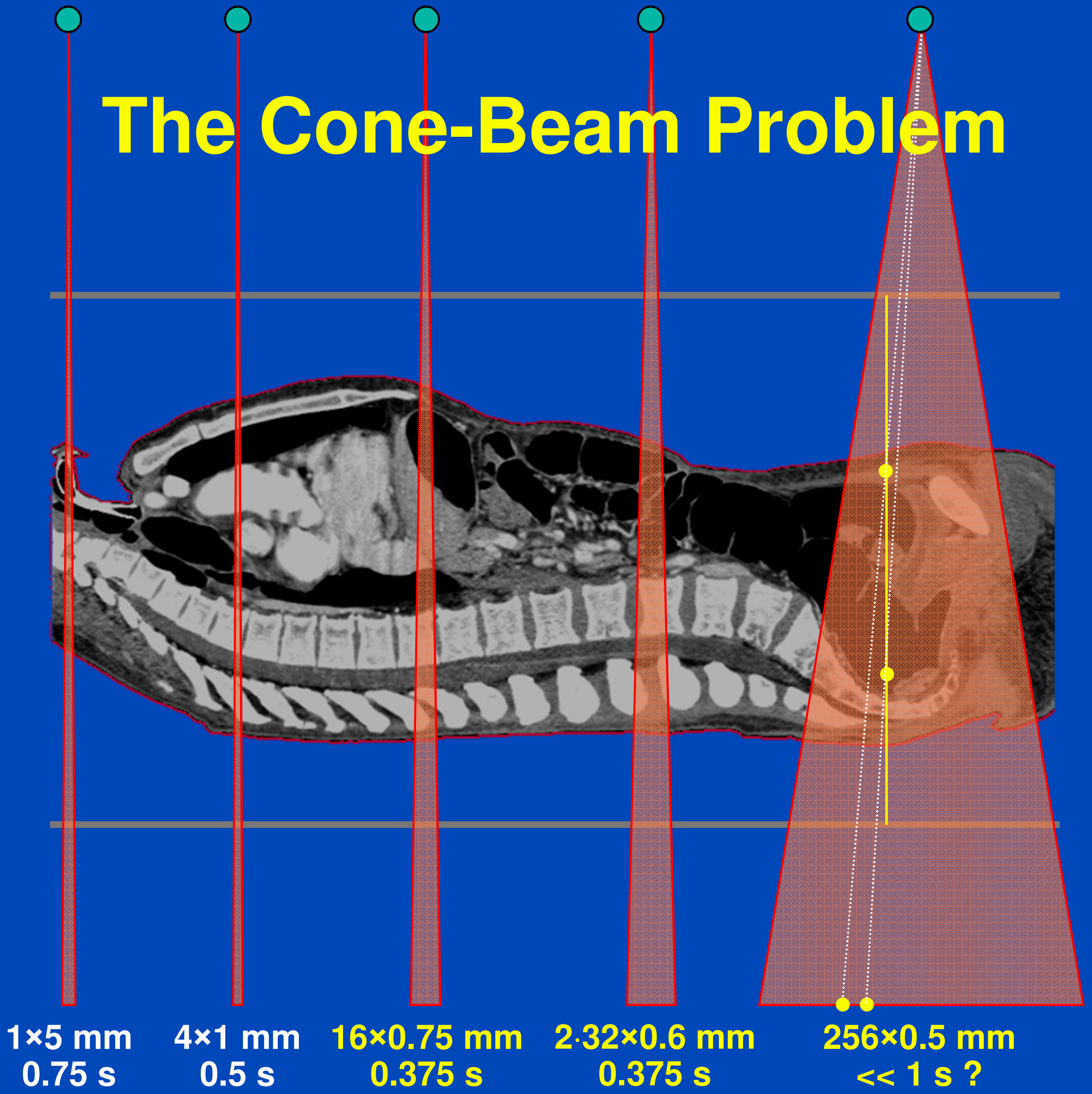
M = 4

120 cm in 40 s

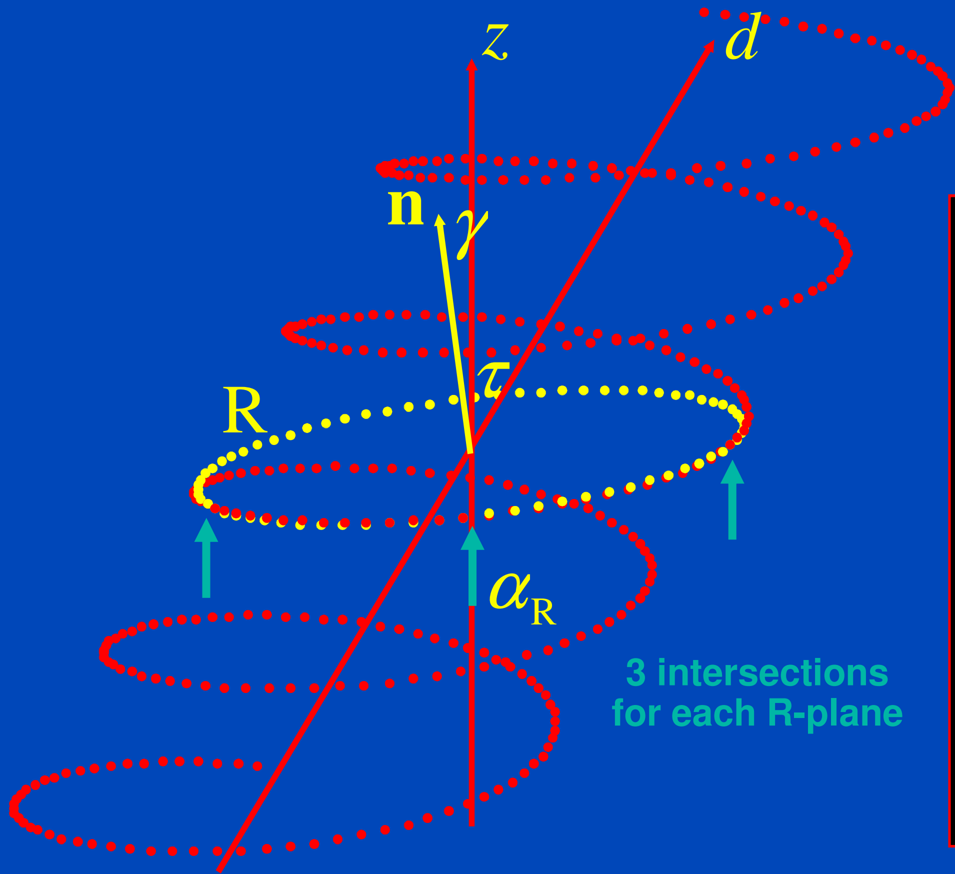
0.5 s per rotation
4×2.5 mm collimation
pitch 1.5


Start of
spiral scan
Scan
trajectory
Direction of
continuous
patient
transport
0
z
0
t
1996:
1×5 mm, 0.75 s
1998:
4×1 mm, 0.5 s
2002:
16×0.75 mm, 0.42 s
2004:
2·32×0.6 mm, 0.33 s

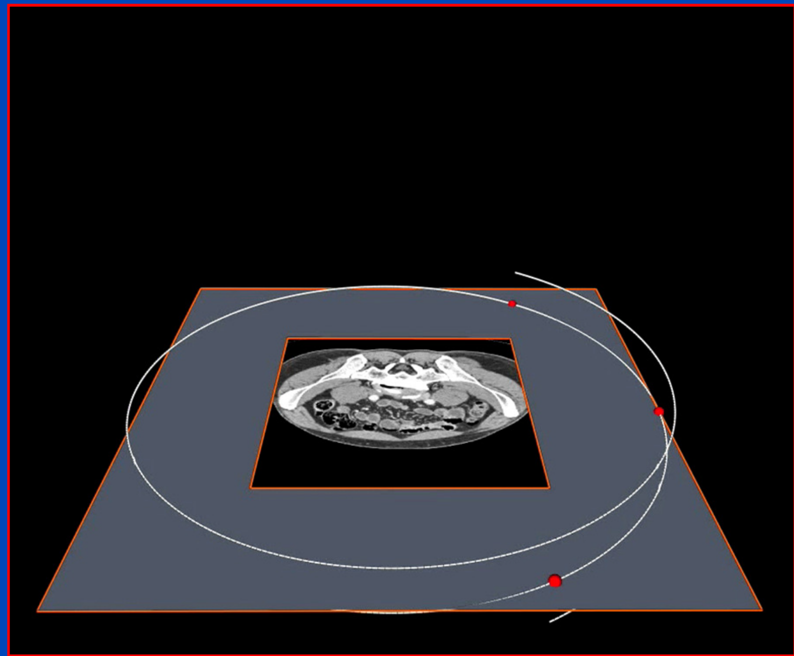
The Cone-Beam Problem



The ASSR Algorithm

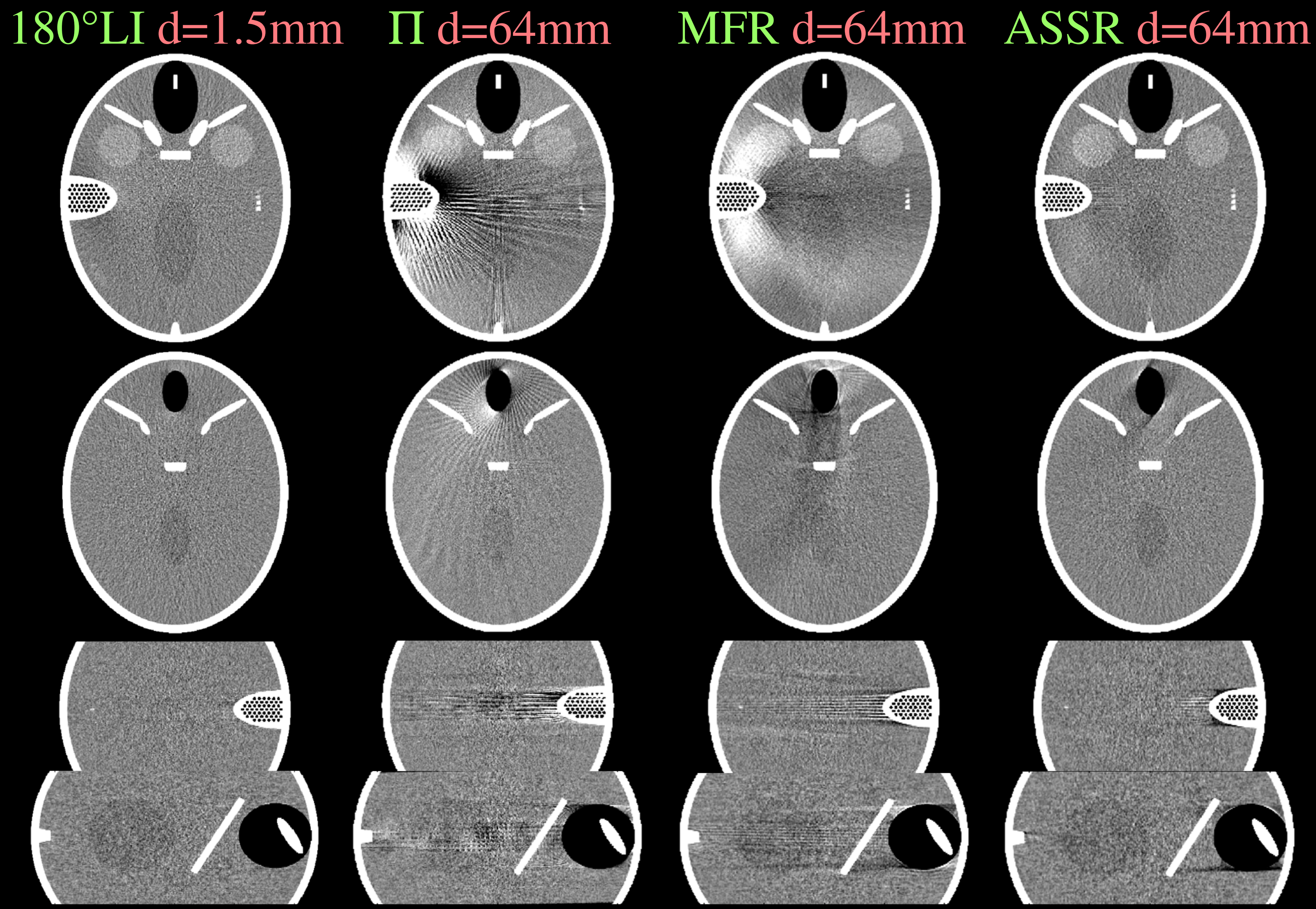


$$p = \frac{d}{MS} \leq 1.5$$



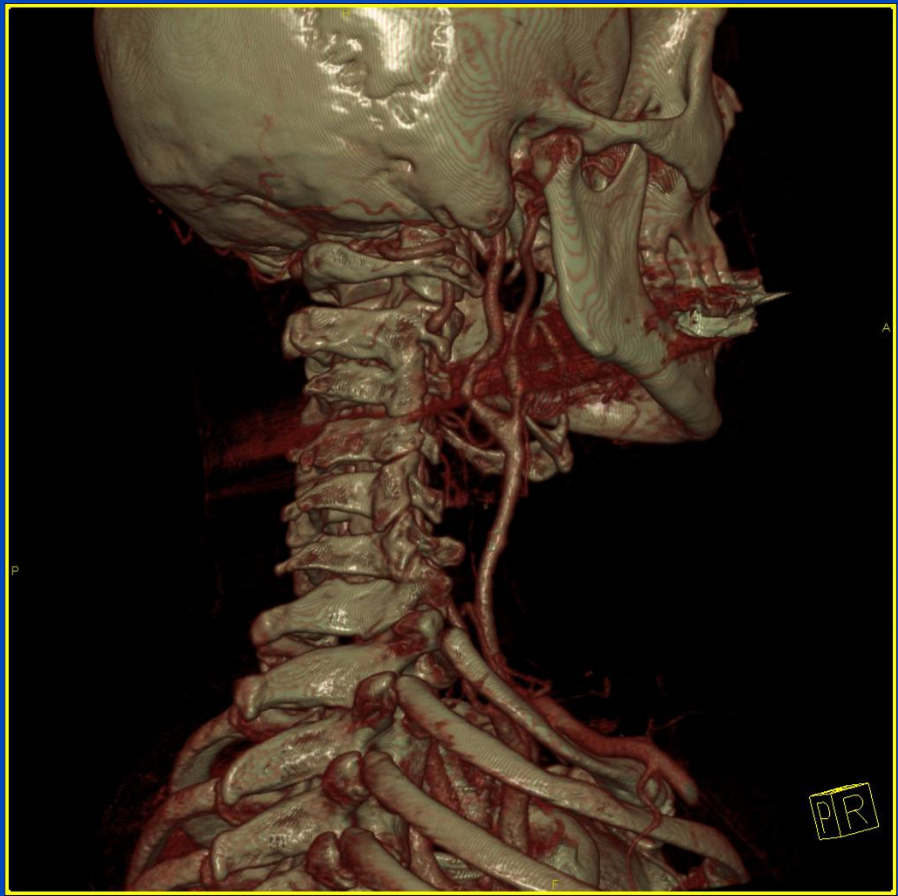
Mean deviation at distance R_M:	$\Delta \approx 0.007 \cdot d$
at distance R_F:	$\Delta \approx 0.014 \cdot d$

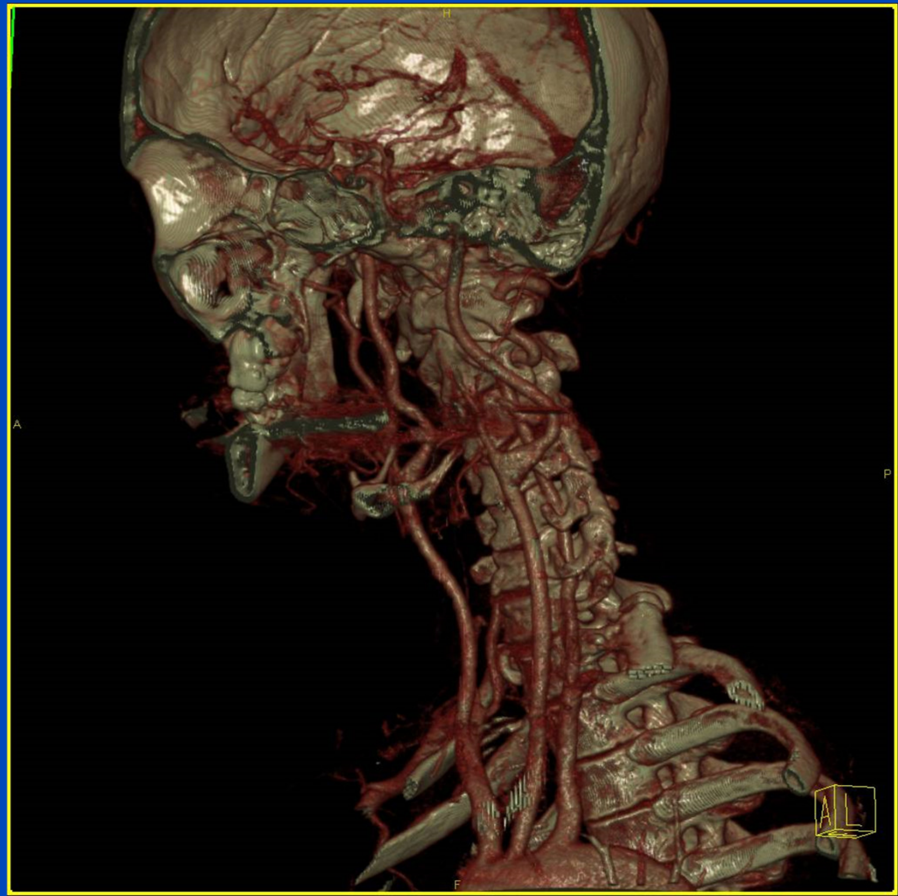
Comparison to Other Approximate Algorithms



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

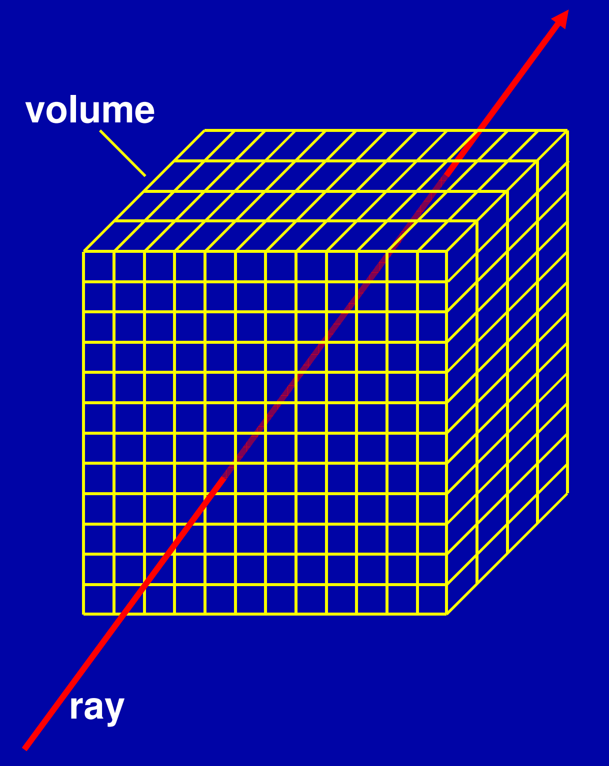
CT-Angiography
Sensation 64 spiral scan with 2·32×0.6 mm and 0.375 s





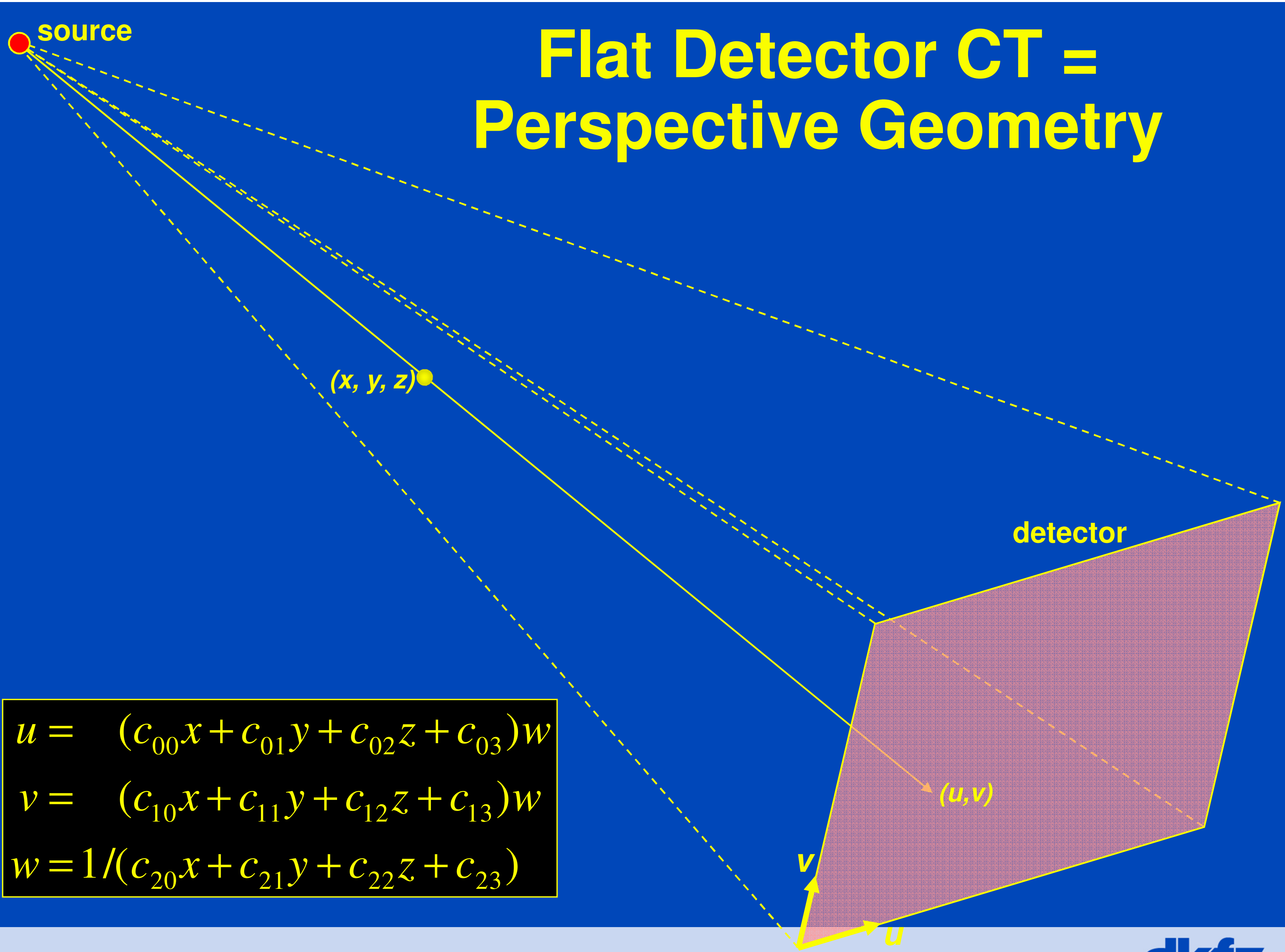
Flat Detector CT = Feldkamp-Type Reconstruction

- **Approximate**
- **Similar to 2D reconstruction:**
  - row-wise filtering of the rawdata
  - followed by backprojection
- **True 3D volumetric backprojection along the original ray direction**
- **Compared to ASSR:**
  - larger cone-angles possible
  - lower reconstruction speed
  - requires 3D backprojection hardware



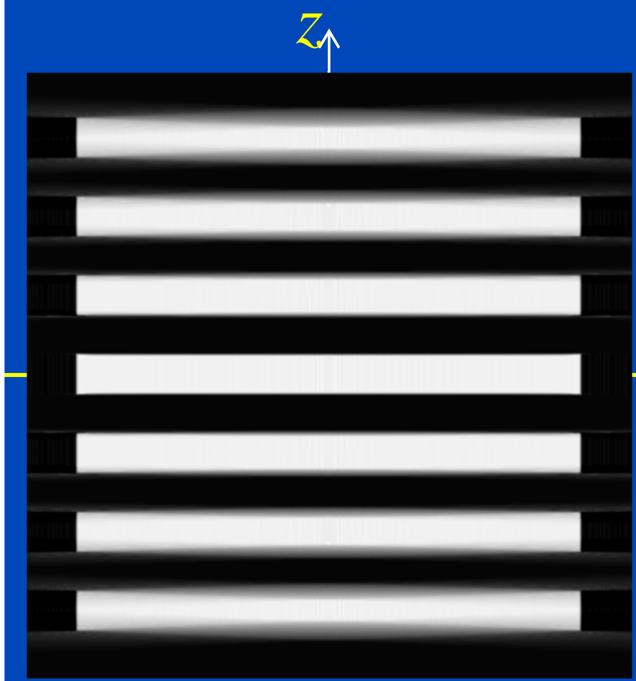
3D backprojection

Flat Detector CT = Perspective Geometry

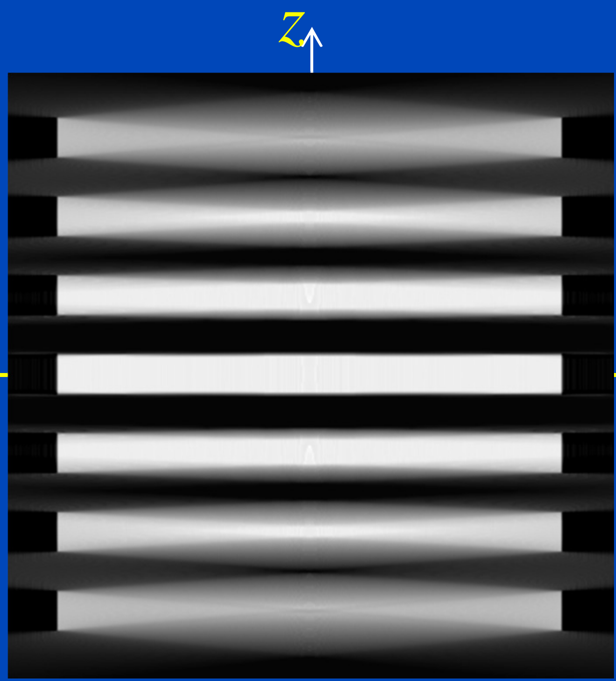


$$u = (c_{00}x + c_{01}y + c_{02}z + c_{03})w$$
$$v = (c_{10}x + c_{11}y + c_{12}z + c_{13})w$$
$$w = 1/(c_{20}x + c_{21}y + c_{22}z + c_{23})$$

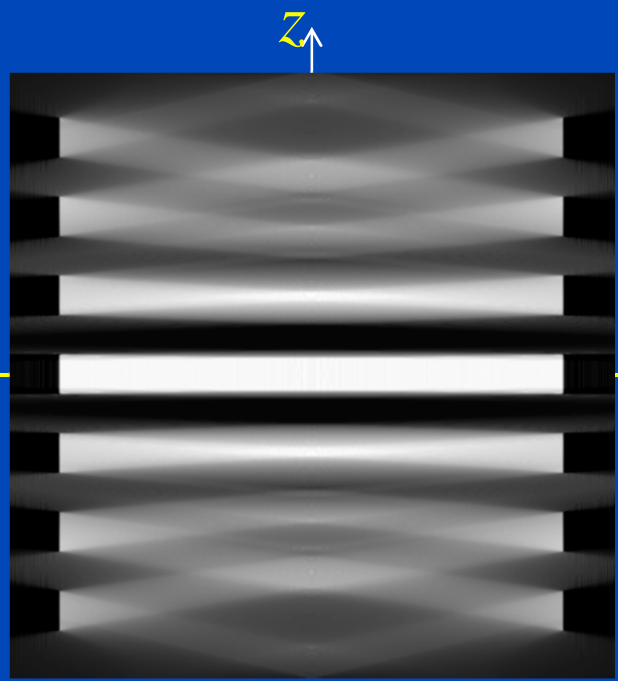
Cone-Beam Artifacts



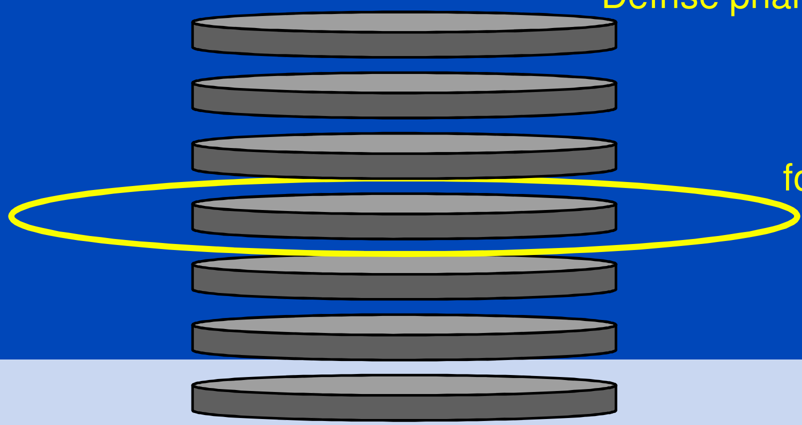
Cone-angle Γ = 6°



Cone-angle Γ = 14°



Cone-angle Γ = 28°



Iterative Image Reconstruction

$$x^2 = y$$

Model

$$x = \sqrt{y}$$

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

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

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

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

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

Update equation

This is an iterative solution.

Influence of Update Equation and Model

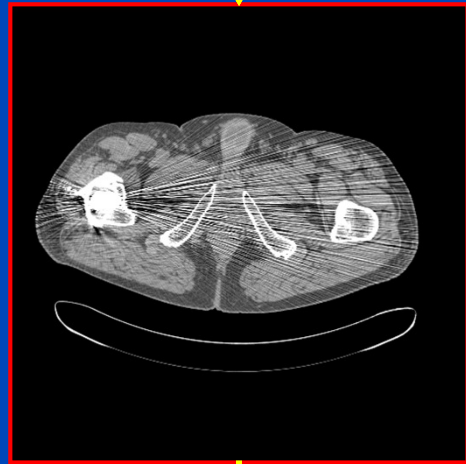
$0.5\,(3 - x_n^2)/x_n$	$0.4\,(3 - x_n^2)/x_n$	$0.5\,(3 - x_n^{2.1})/x_n$
$x_0 = 1.$	$x_0 = 1.$	$x_0 = 1.$
$x_1 = 2.$	$x_1 = 1.8$	$x_1 = 2.$
$x_2 = 1.75$	$x_2 = 1.74667$	$x_2 = 1.67823$
$x_3 = 1.73214$	$x_3 = 1.73502$	$x_3 = 1.68833$
$x_4 = 1.73205$	$x_4 = 1.73265$	$x_4 = 1.68723$
$x_5 = 1.73205$	$x_5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

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

Kaczmarz‘s Method = ART

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

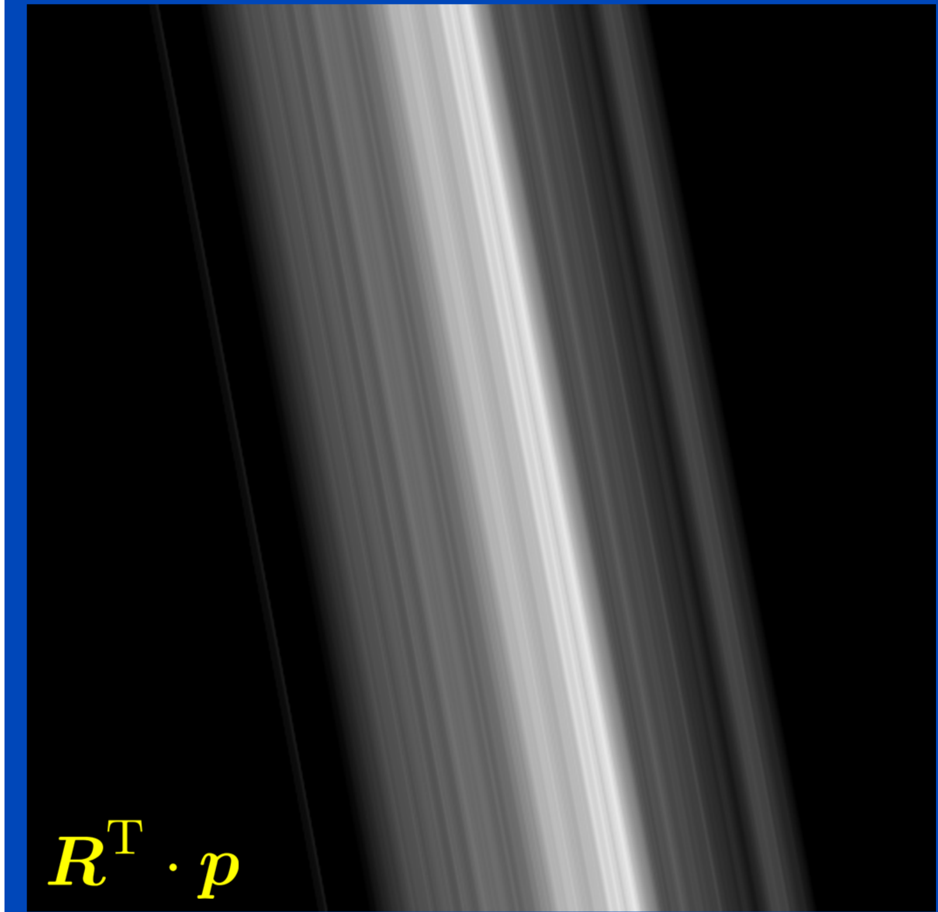
apply inverse model

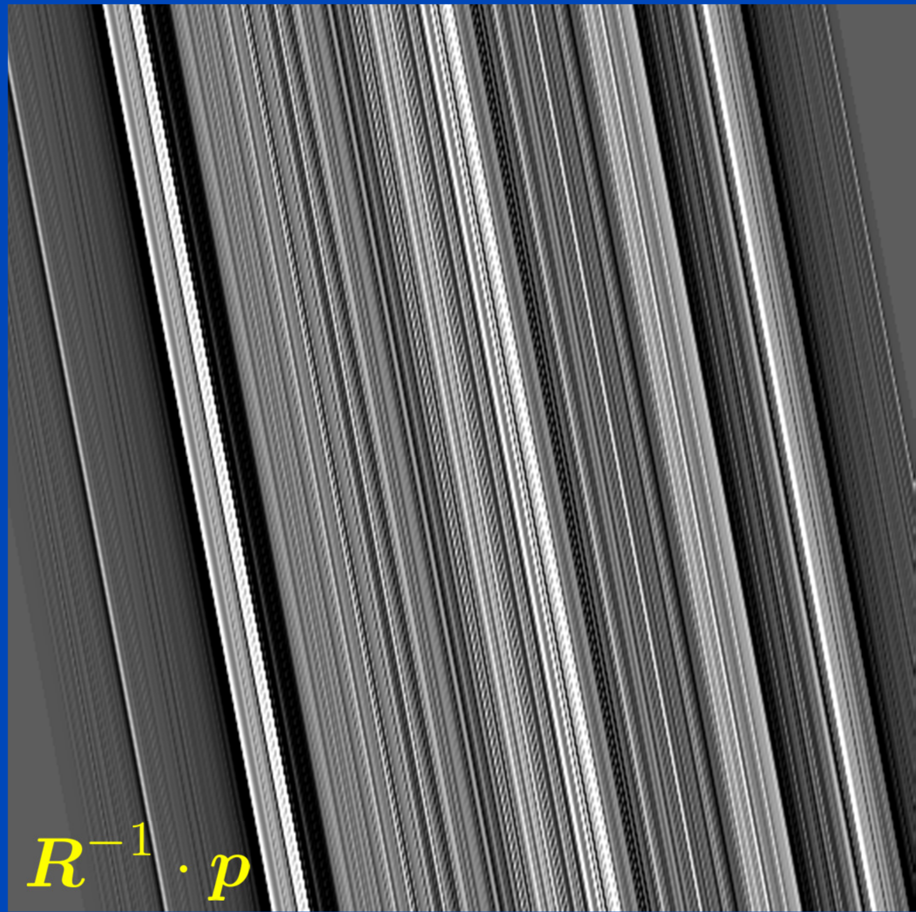


apply forward model

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

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 …**

Bayesian Reconstruction

= statistical reconstruction

- Finding an image *f* such that the probability of *f* given the projection data *p*, i.e. $P(\boldsymbol{f}|\boldsymbol{p})$, is maximized is difficult.
- Since we know from Bayes that

$$P(\boldsymbol{f}|\boldsymbol{p})P(\boldsymbol{p}) = P(\boldsymbol{p}|\boldsymbol{f})P(\boldsymbol{f})$$

  we may as well maximize $P(\boldsymbol{p}|\boldsymbol{f})$, because without further information the a priori probabilities introduce nothing but a positive factor of proportionality.
- If we have further information, e.g. on *f*, we may incorporate this prior knowledge and maximize the a posteriori probability $P(\boldsymbol{p}|\boldsymbol{f})P(\boldsymbol{f})$ instead.
- In log domain this becomes

$$\boldsymbol{f} = \arg\min_{\boldsymbol{f}} \Big(L(\boldsymbol{p}|\boldsymbol{f}) + L(\boldsymbol{f}) \Big)$$

ML MAP

Objective Function: Gauß Model

- **Assume that the attenuation is Gaussian-distributed**

$$\mathcal{L}(A) = \mathcal{N}(\sigma, \boldsymbol{r} \cdot \boldsymbol{f})$$

i.e. $P(A = a) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(a-\mu)^2/\sigma^2}$ **with** $\mu = \boldsymbol{r} \cdot \boldsymbol{f}$ **.**

- **Consequently, the likelihood for all *N* measured signals is (** $\mu_n = \boldsymbol{r}_n \cdot \boldsymbol{f}$ **):**

$$P(\boldsymbol{A} = \boldsymbol{a}, \boldsymbol{f}) = \prod_n P(A_n = a_n)$$

- **Before maximizing take the log, penalize roughness,**

$$L(\boldsymbol{f}) = -\sum_n \left(\frac{a_n - \mu_n}{\sigma_n} \right)^2 - \beta R(\boldsymbol{f})$$

and then find the image *f* that maximizes *L*.

Gauß Model (continued)

- This leads us to minimizing

$$(\boldsymbol{R} \cdot \boldsymbol{f} - \boldsymbol{a})^{\mathrm{T}} \cdot \boldsymbol{D} \cdot (\boldsymbol{R} \cdot \boldsymbol{f} - \boldsymbol{a})$$

  which means solving

$$\boldsymbol{R}^{\mathrm{T}} \cdot \boldsymbol{D} \cdot (\boldsymbol{R} \cdot \boldsymbol{f} - \boldsymbol{a}) = \boldsymbol{0}$$

- This must be done numerically (e.g. Jacobi method) and the solutions are often of type

$$\boldsymbol{f}_{\nu+1} = \boldsymbol{f}_{\nu} + \mathrm{diag}(\boldsymbol{u}) \cdot \boldsymbol{R}^{\mathrm{T}} \cdot \mathrm{diag}(\boldsymbol{v}) \cdot (\boldsymbol{a} - \boldsymbol{R} \cdot \boldsymbol{f}_{\nu})$$

Update Equation: Gauß Model

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

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

- **and many more …**

Objective Function: Poisson Model

- **Assume that the intensities are Poisson-distributed**

$$\mathcal{L}(I) = \mathcal{P}(I_0 e^{-\boldsymbol{r} \cdot \boldsymbol{f}})$$

which means $P(I = i) = \frac{\mu^i}{i!} e^{-\mu}$ **with** $\mu = I_0 e^{-\boldsymbol{r} \cdot \boldsymbol{f}}$ **.**

- **Consequently, the likelihood for all *N* measured signals is (** $\mu_n = I_0 e^{-\boldsymbol{r}_n \cdot \boldsymbol{f}}$ **):**

$$P(\boldsymbol{I} = \boldsymbol{i}, \boldsymbol{f}) = \prod_n P(I_n = i_n) = \prod_n \frac{\mu_n^{i_n}}{i_n!} e^{-\mu_n}$$

- **Before maximizing take the log, penalize roughness,**

$$L(\boldsymbol{f}) = \sum_n (i_n \ln \mu_n - \mu_n) - \beta R(\boldsymbol{f})$$

and then find the image *f* that maximizes *L*.

Update Equation: Poisson Model

- **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 many more …**

Iterative Reconstruction: Parameters

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

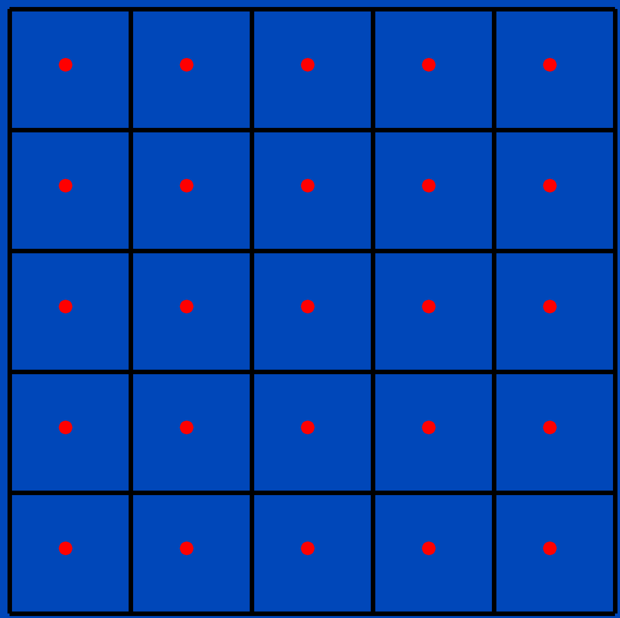
$$f(x,y) = \sum_m f_m b(x - x_m, y - y_m)$$

- 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

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

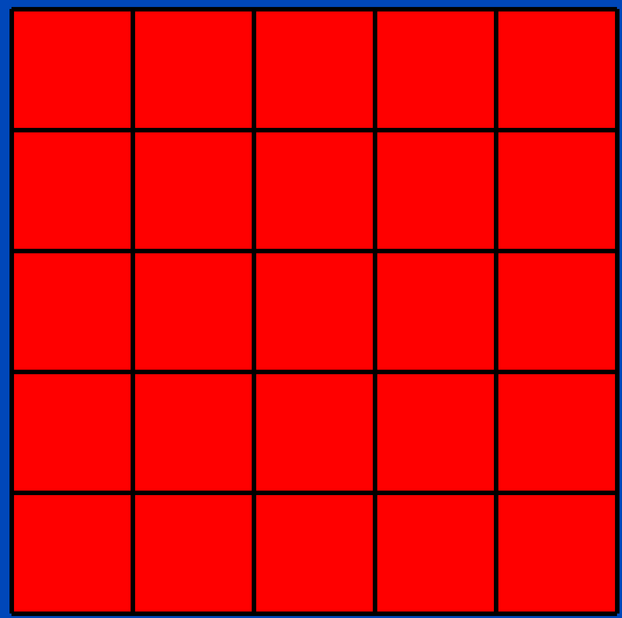
- Inverse model (backprojection)
  - Transpose of forward model
  - Pixel-driven backprojection
  - Filtered backprojection
  - …

Image Representation



$$b(x, y) =$$ •

Image Representation



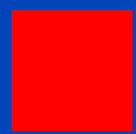
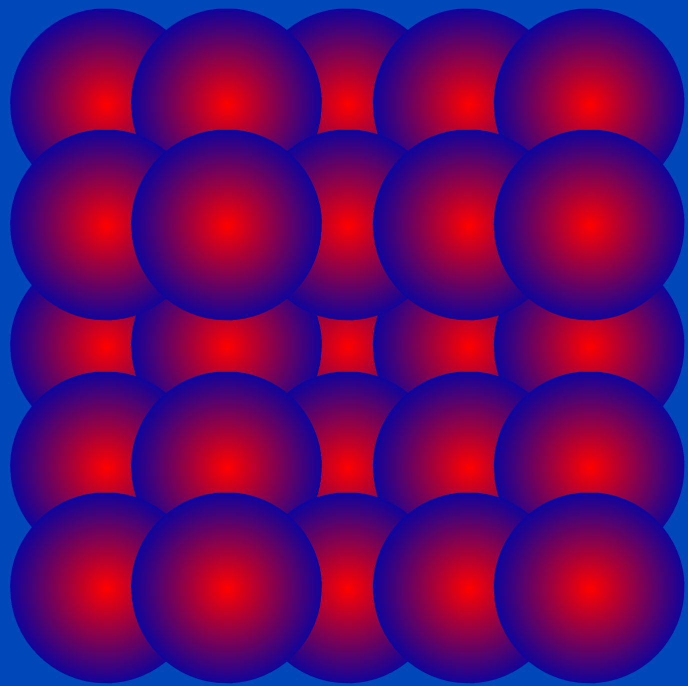
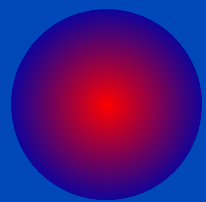
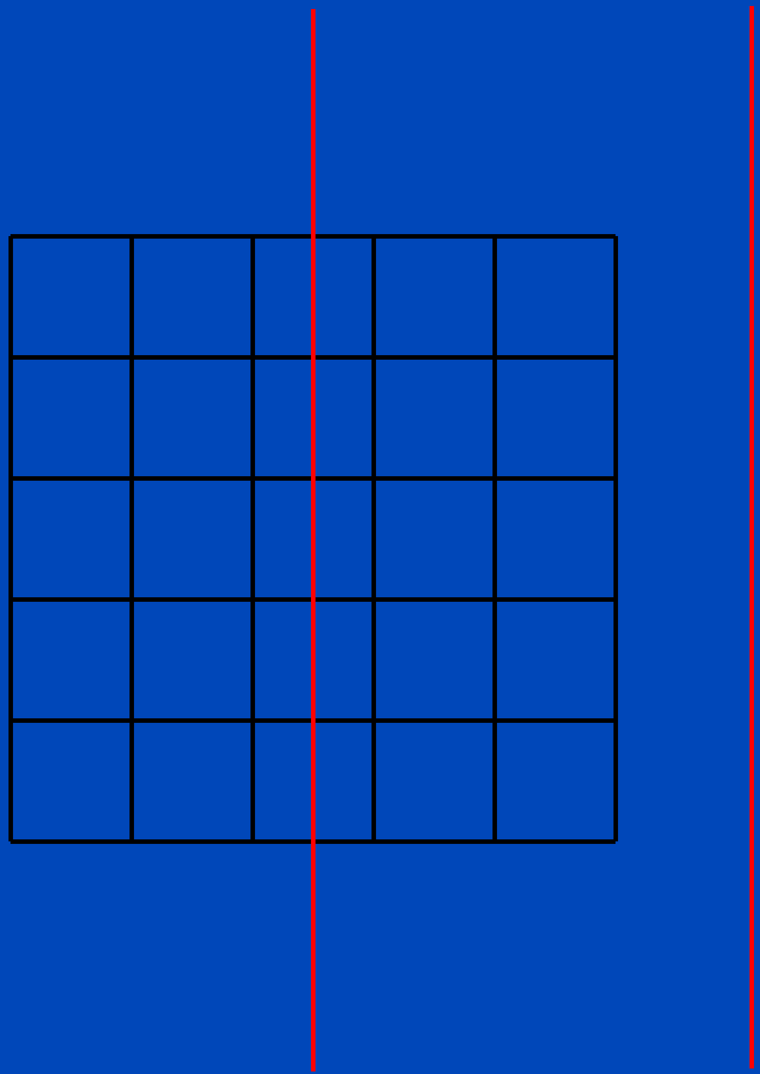
$b(x, y) =$ 

Image Representation

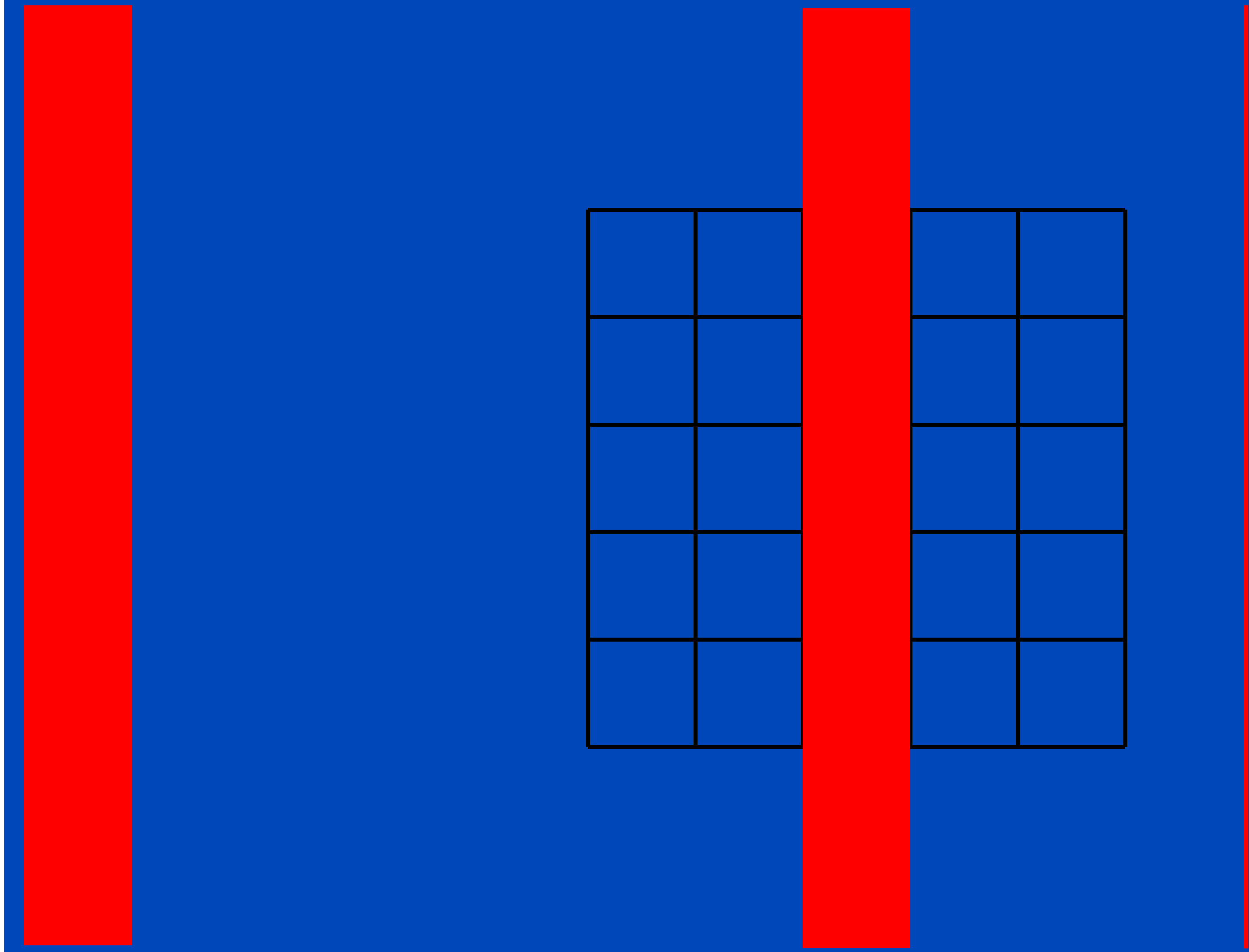


$b(x, y) =$ 

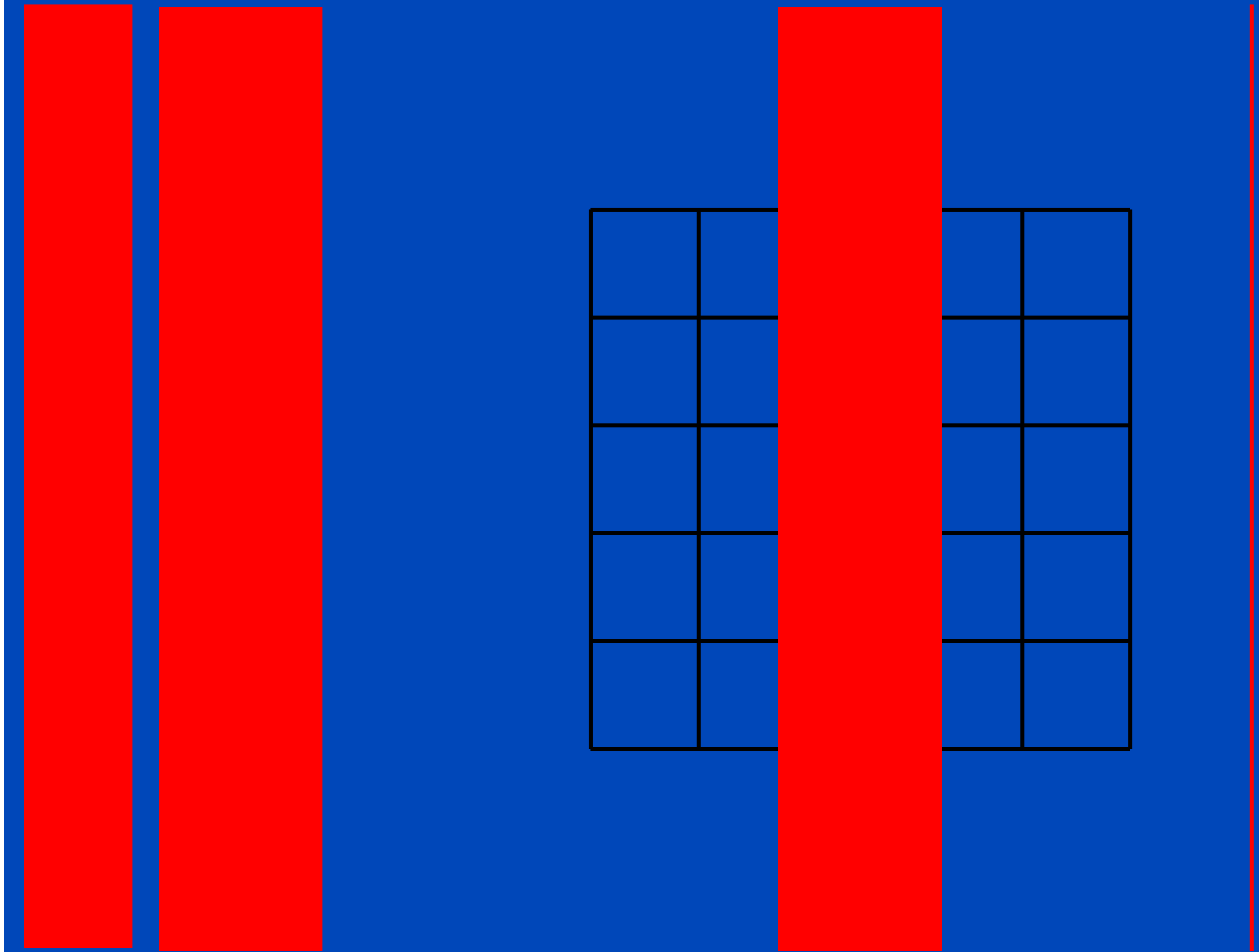
Forward Model: Beam Shape



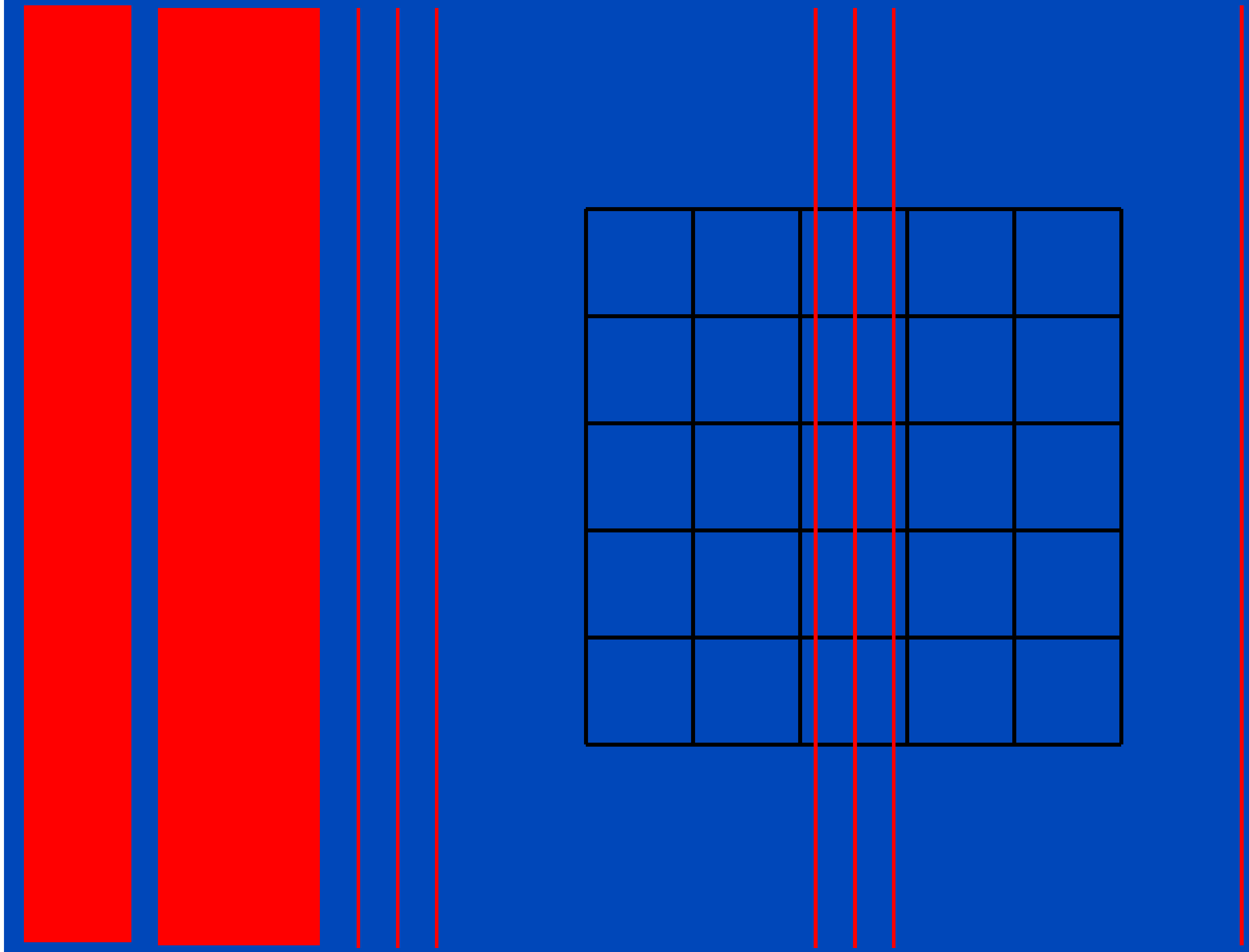
Forward Model: Beam Shape



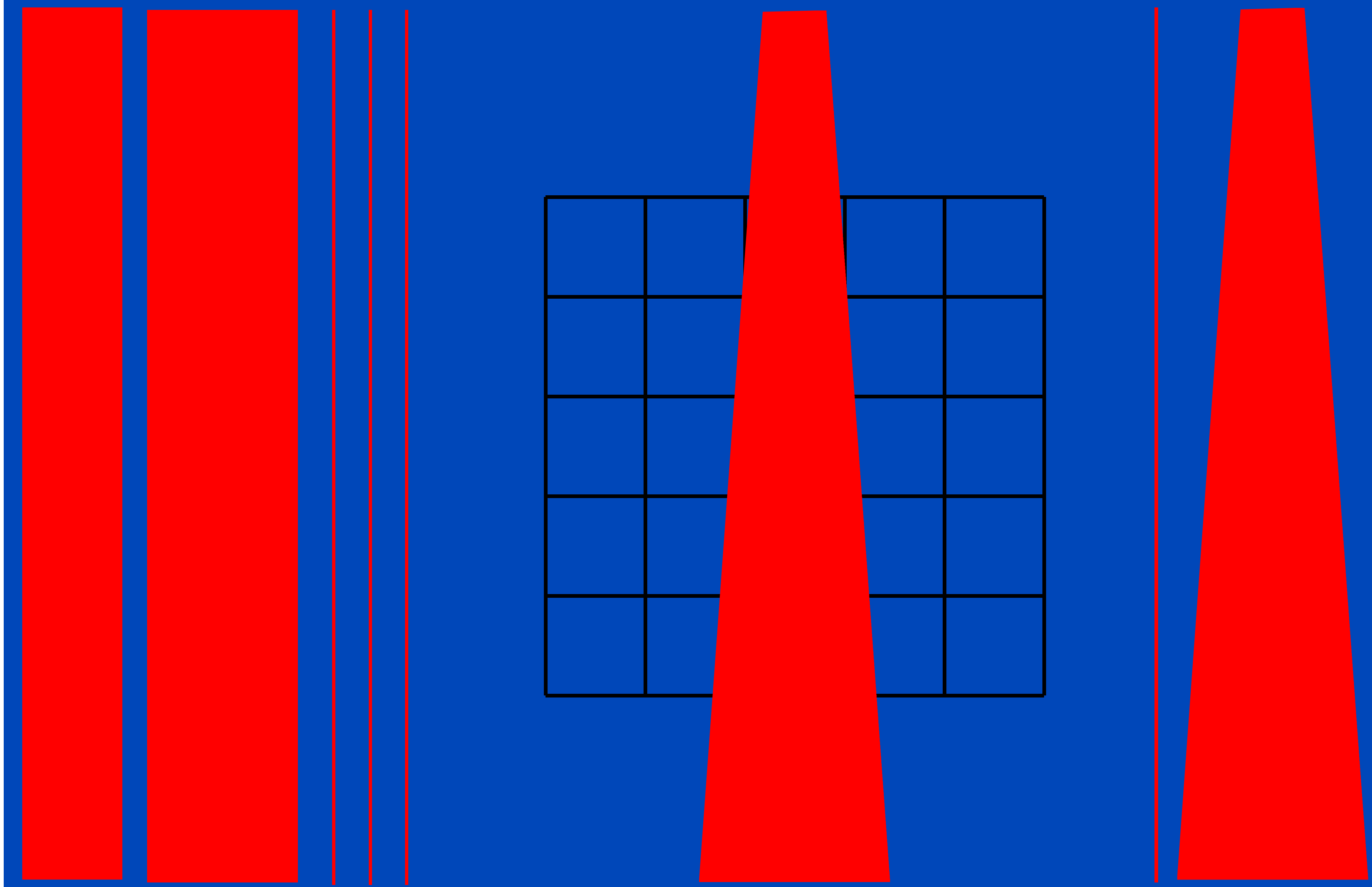
Forward Model: Beam Shape



Forward Model: Beam Shape



Forward Model: Beam Shape



Forward Model: Beam Shape

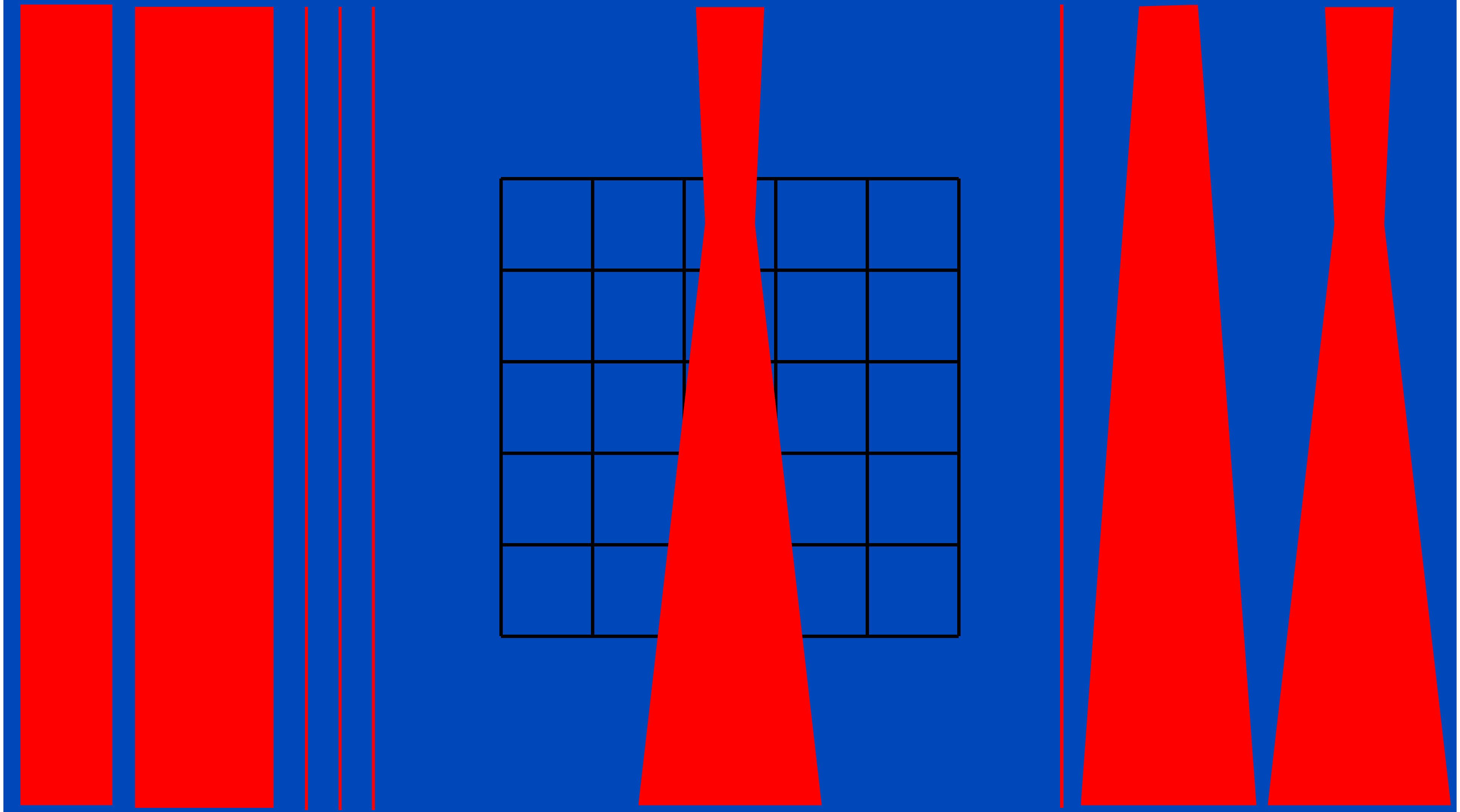
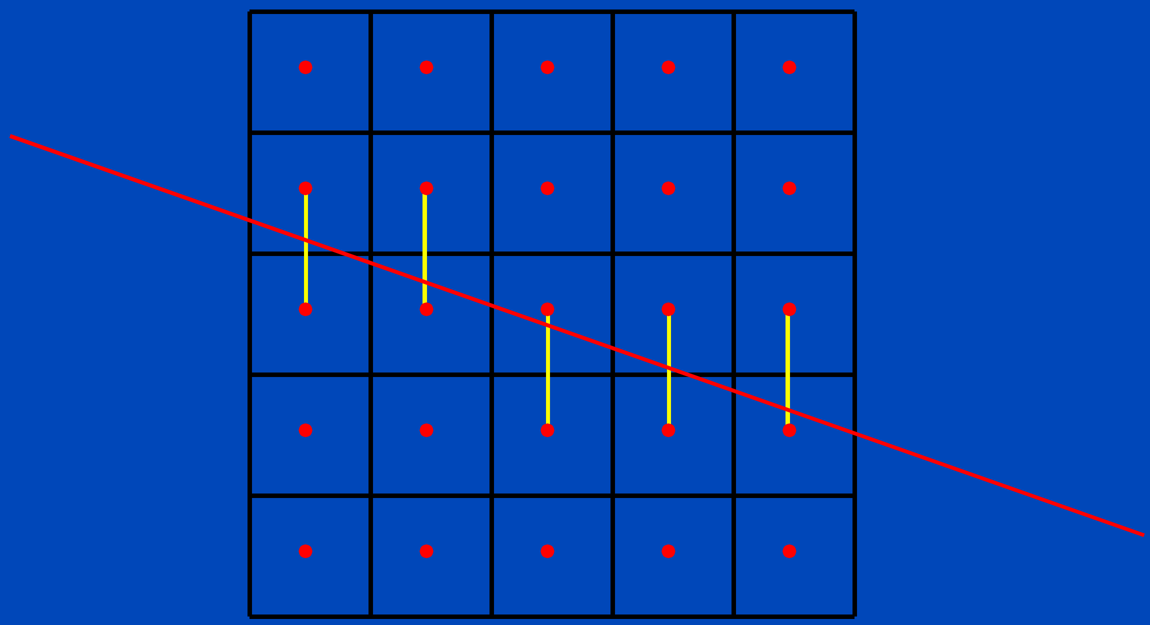


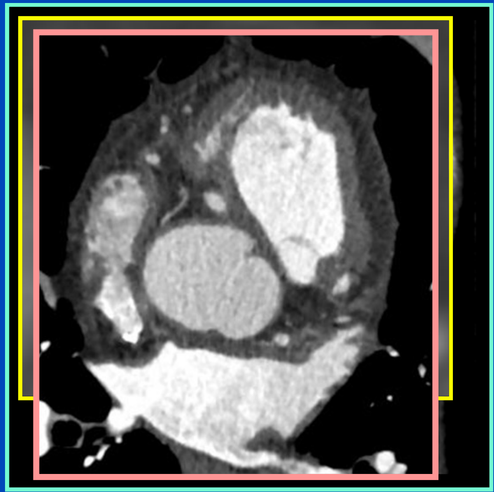
Image Representation and Forward Model are Linked!

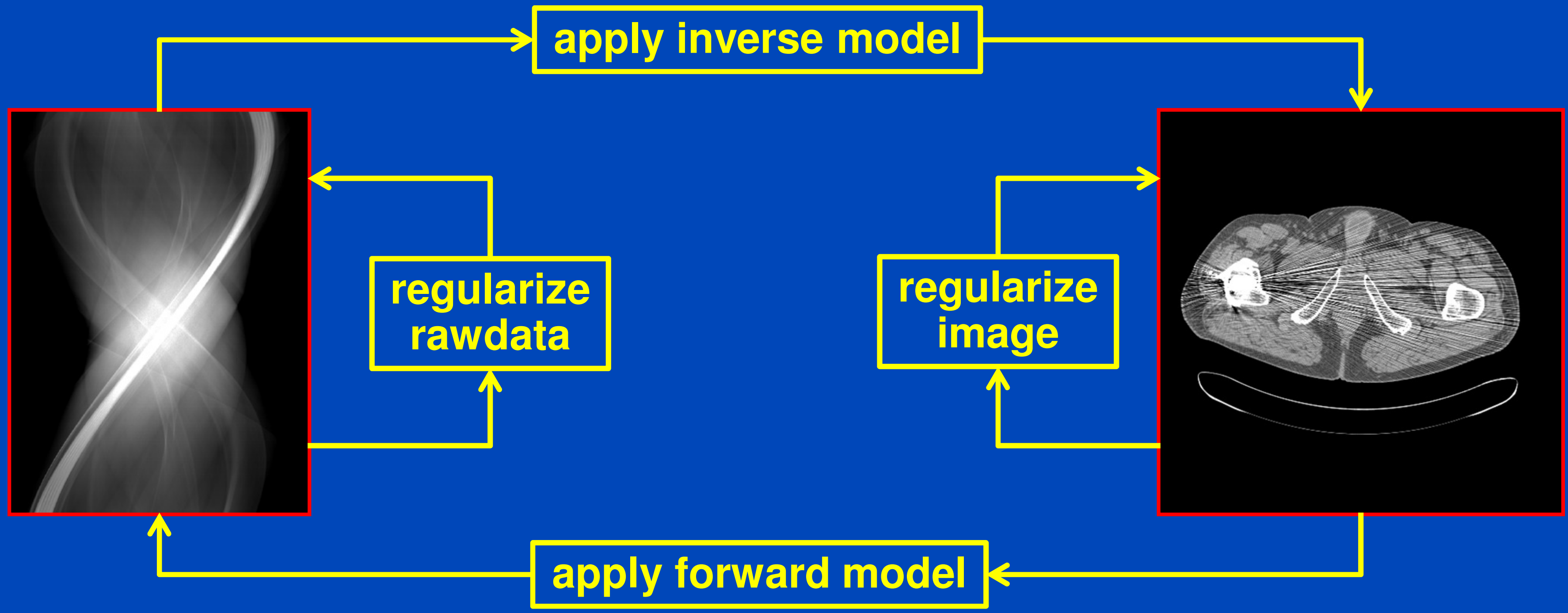


Joseph's forward projector

Iterative Reconstruction

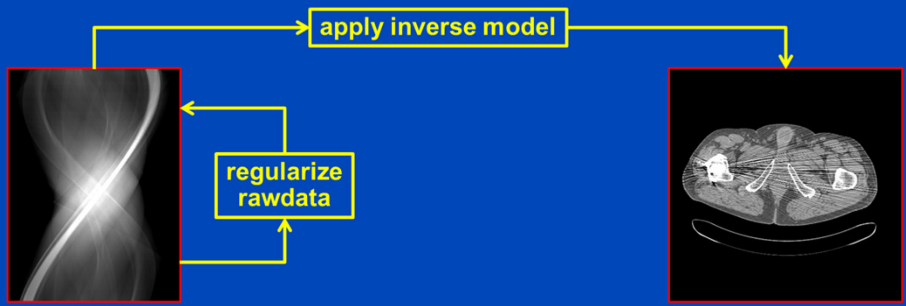
- Aim: less artifacts, lower noise, lower dose
- Iterative reconstruction
  - Reconstruct an image.
  - Does the image correspond to the rawdata?
  - If not, reconstruct a correction image and continue.
- SPECT + PET are iterative for a long time!
- CT product implementations
  - ASIR (adaptive statistical 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)



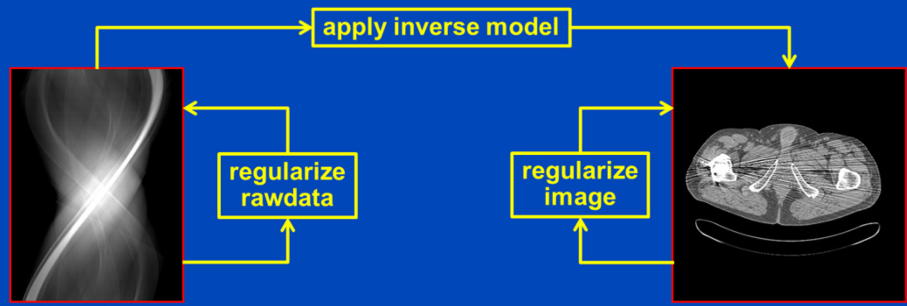


- Rawdata regularization: adaptive filtering[1], precorrections, filtering of update sinograms...
- Inverse model: backprojection (R^T) or filtered backprojection (R^{-1}). In clinical CT, where the data are of high fidelity and nearly complete, one would prefer filtered backprojection to increase convergence 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, …

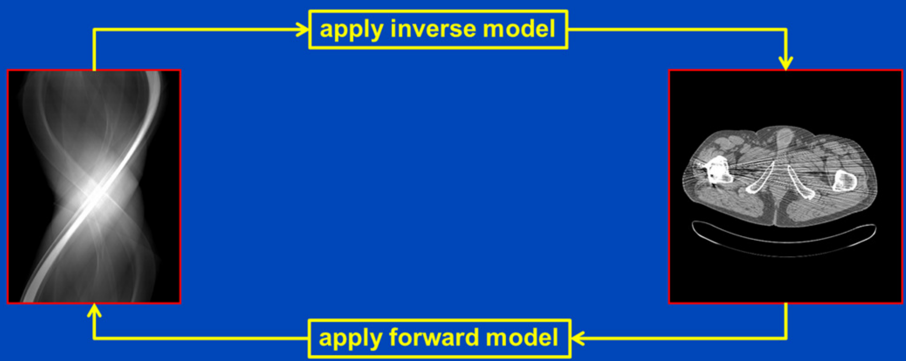
[1]M. Kachelrieß et al., Generalized Multi-Dimensional Adaptive Filtering, MedPhys 28(4), 2001



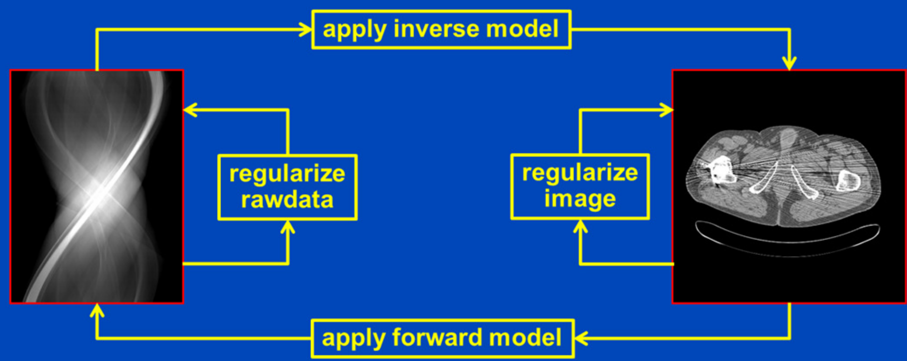
Conventional FBP with rawdata denoising (all vendors)



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



Veo/MBIR (Ge)

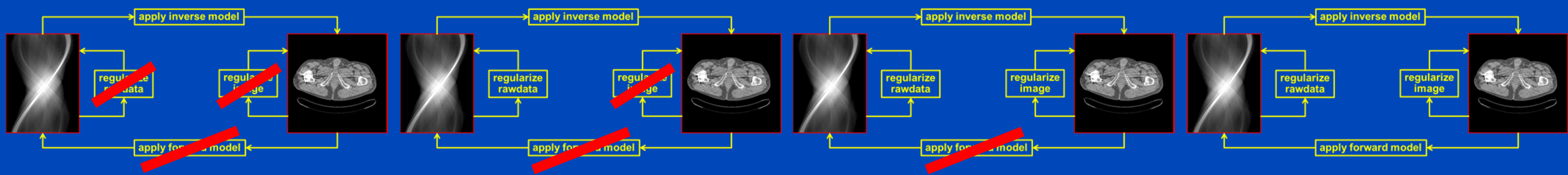


IMR (Philips), SAFIRE, ADMIRE (Siemens), FIRST (Toshiba)

M. Kachelrieß. Current Cardiovascular Imaging Reports 6:268–281, 2013

Plain FBP	Siemens Standard	IRIS VA34	SAFIRE VA40

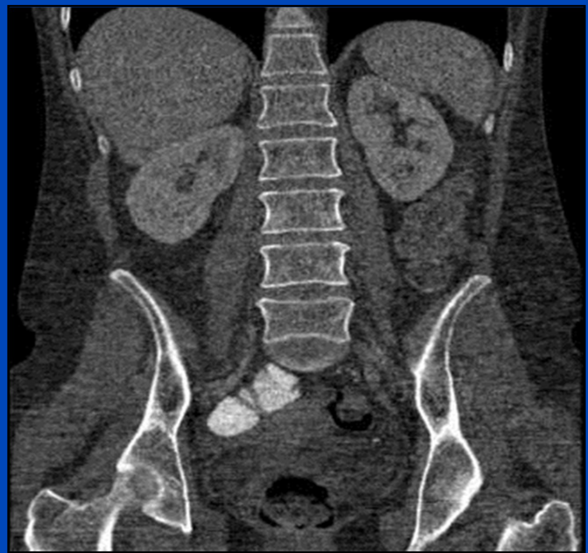
σ = 26.8 HU	σ = 17.6 HU	σ = 12.3 HU	σ = 7.8 HU

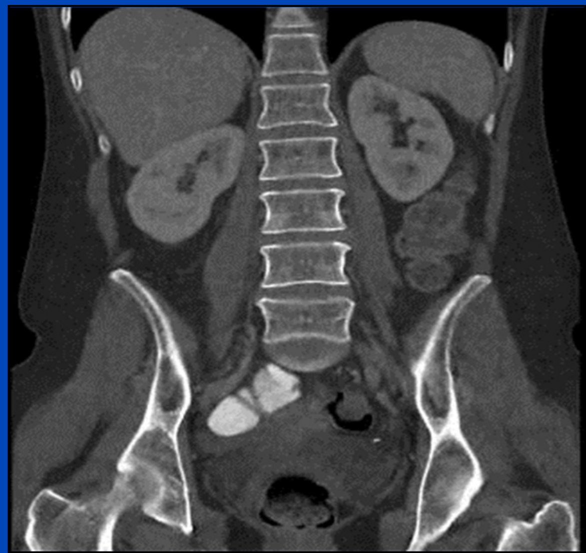


CT images provided by Siemens Healthcare, Forchheim, Germany

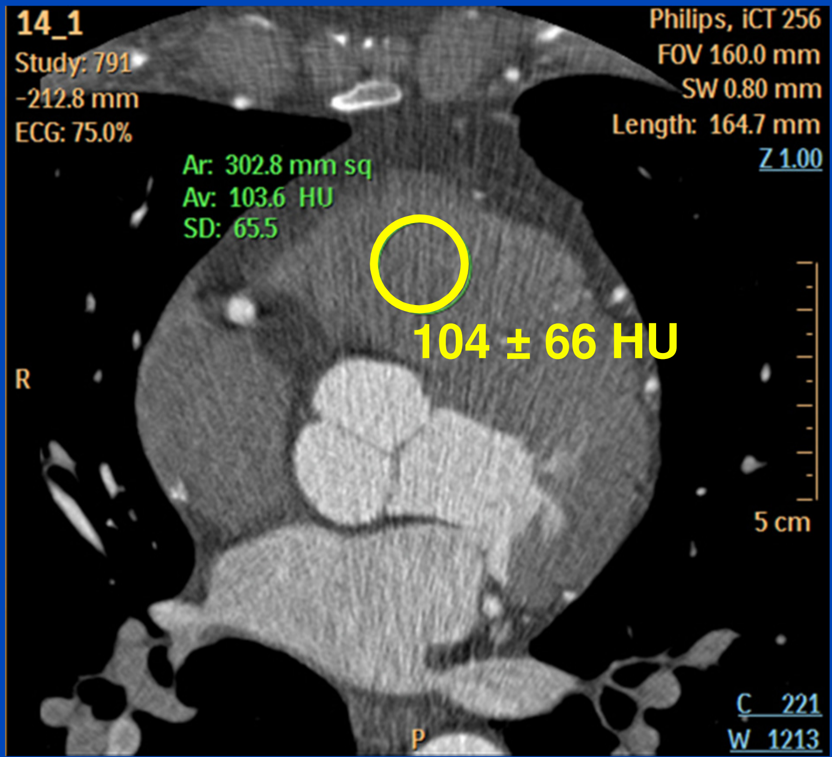
dkfz.

FBP ASIR Veo

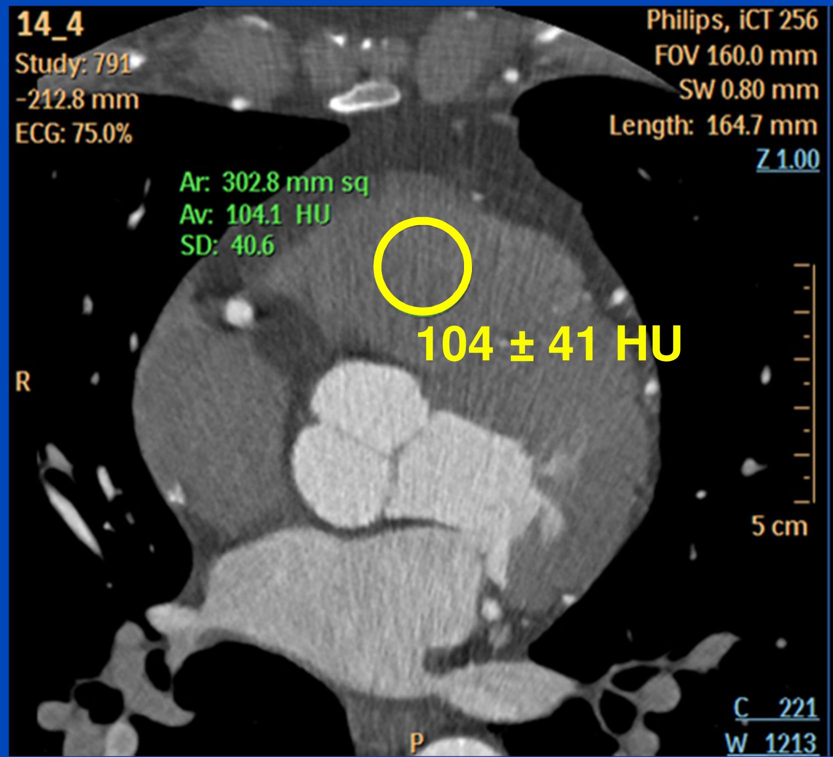




Filtered Backprojection



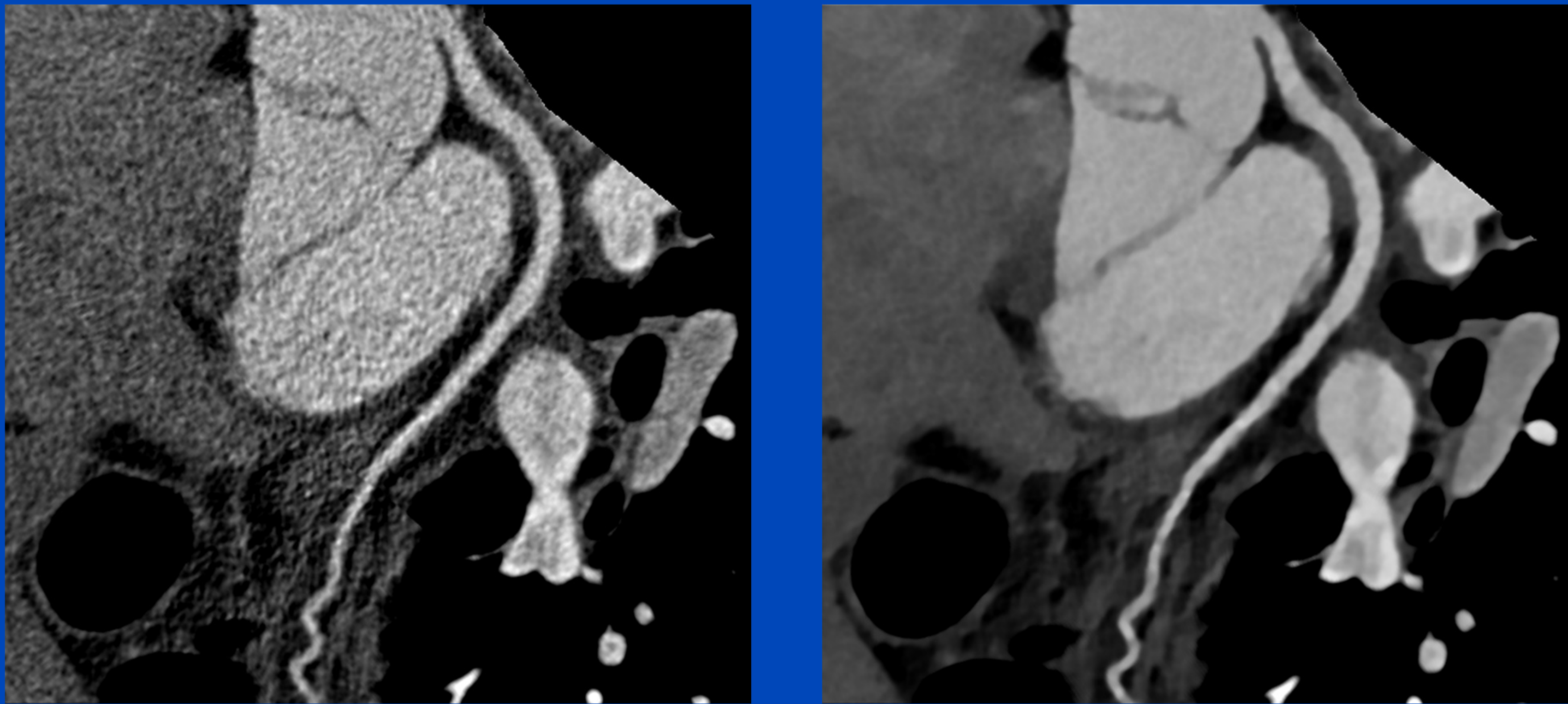
iDose 60%



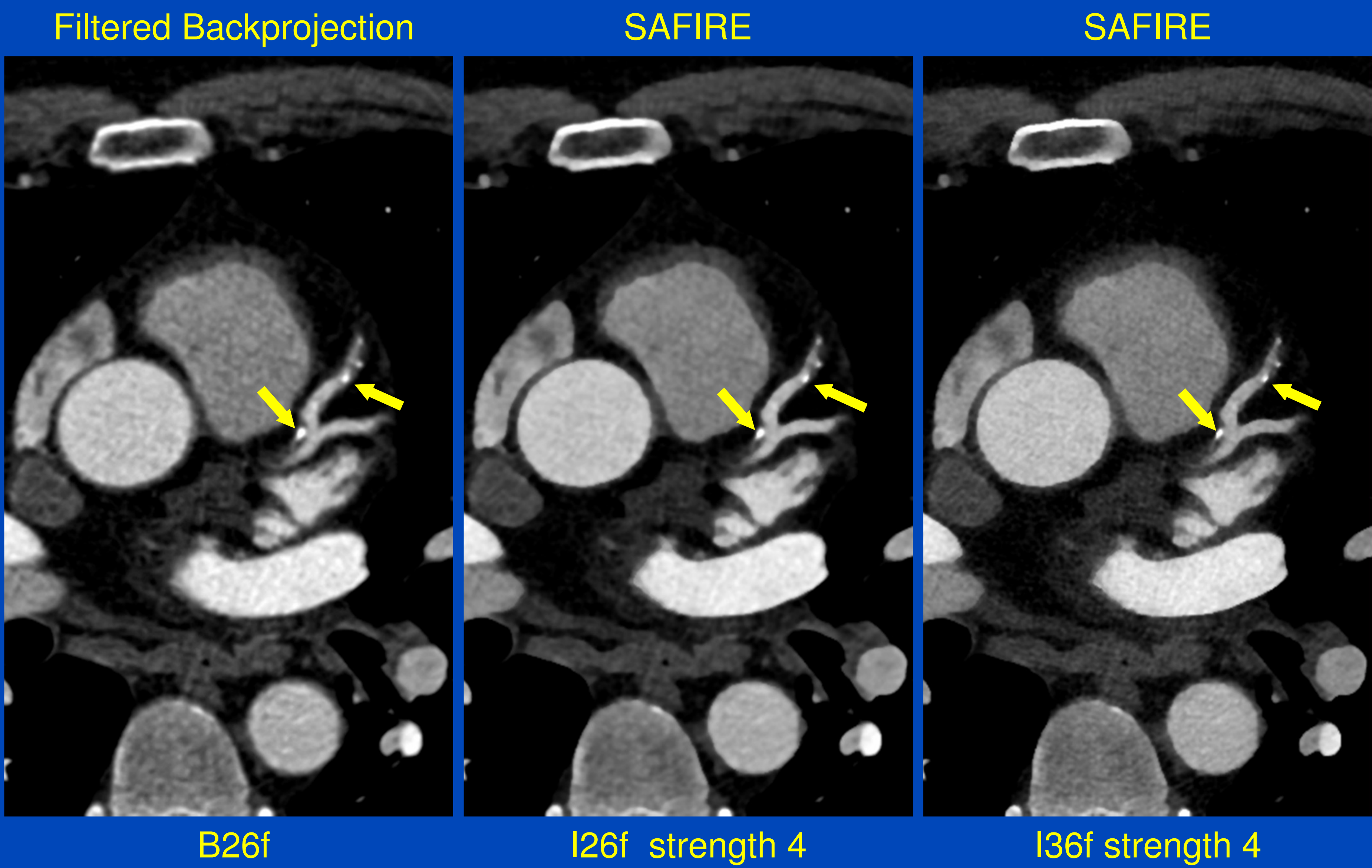
Courtesy of Dr. Waldemar Hosch, Zürich, Switzerland.

FBP

IMR

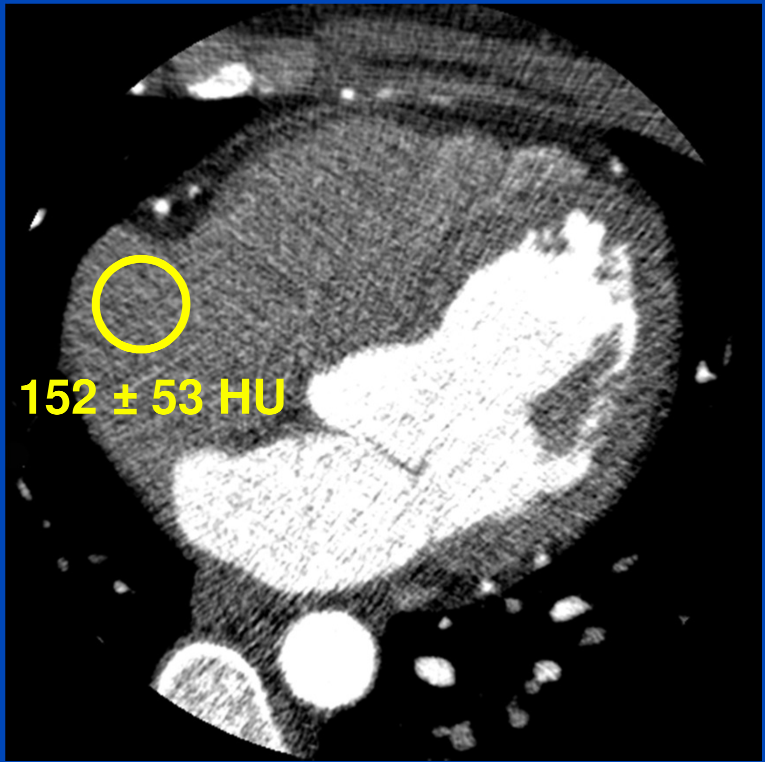


Courtesy of Dr. Thomas Köhler, Philips, Germany.

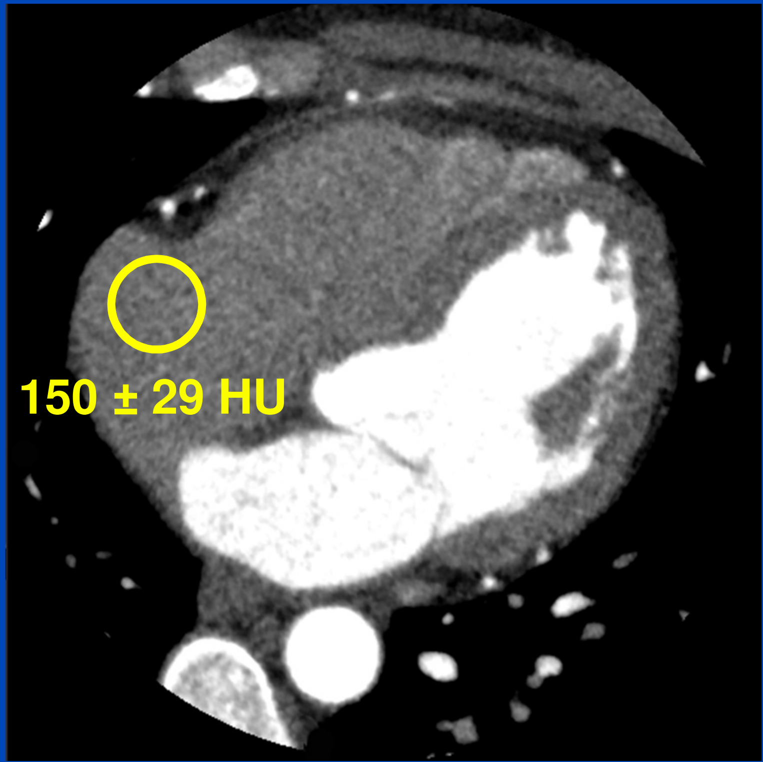


Courtesy of Siemens Healthcare, Forchheim, Germany.

Filtered Backprojection



AIDR3D



Filtered Backprojection

AIDR3D mild

AIDR3D standard

Advantages of SAFIRE versus Linear Noise Reduction

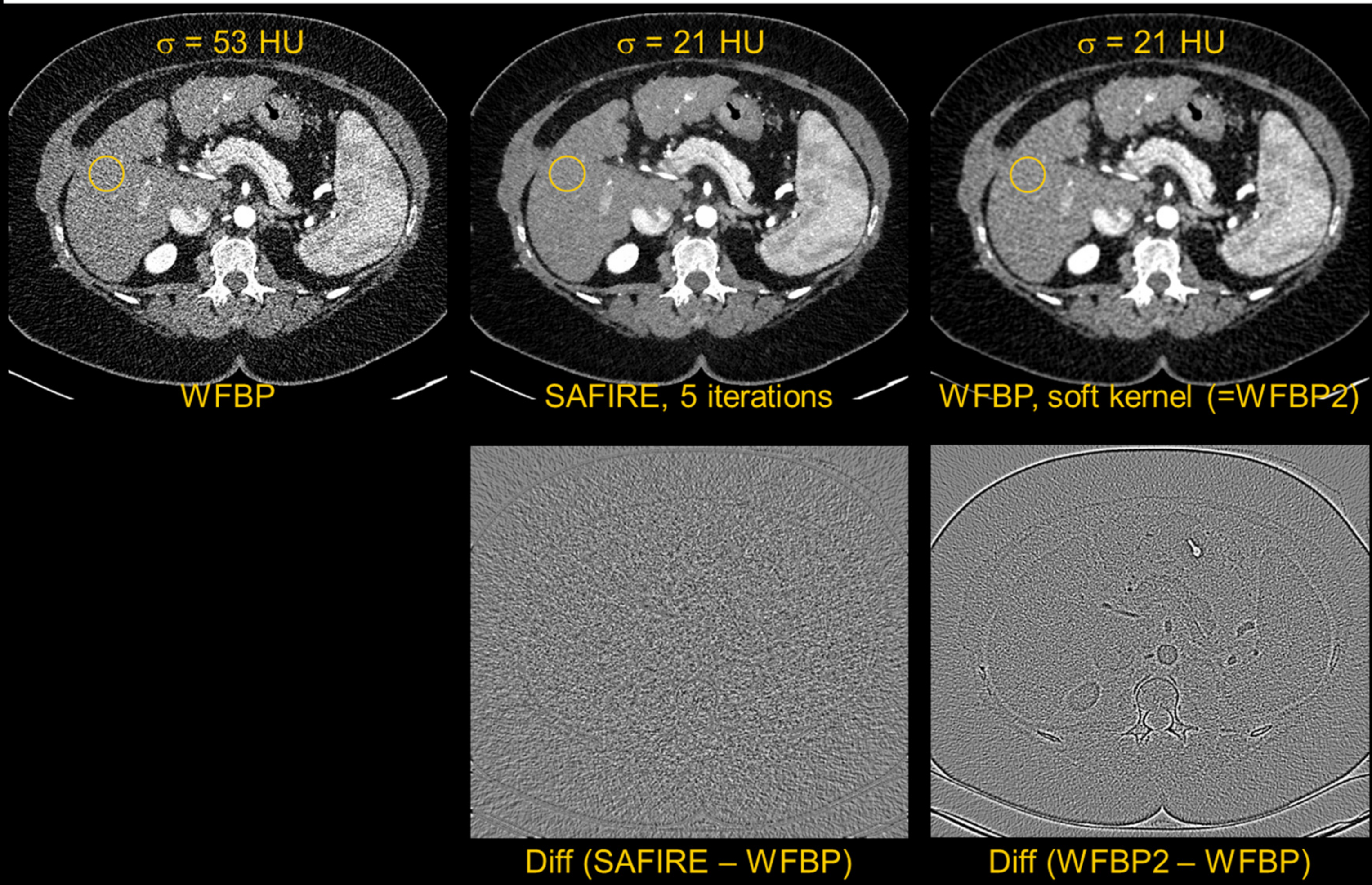
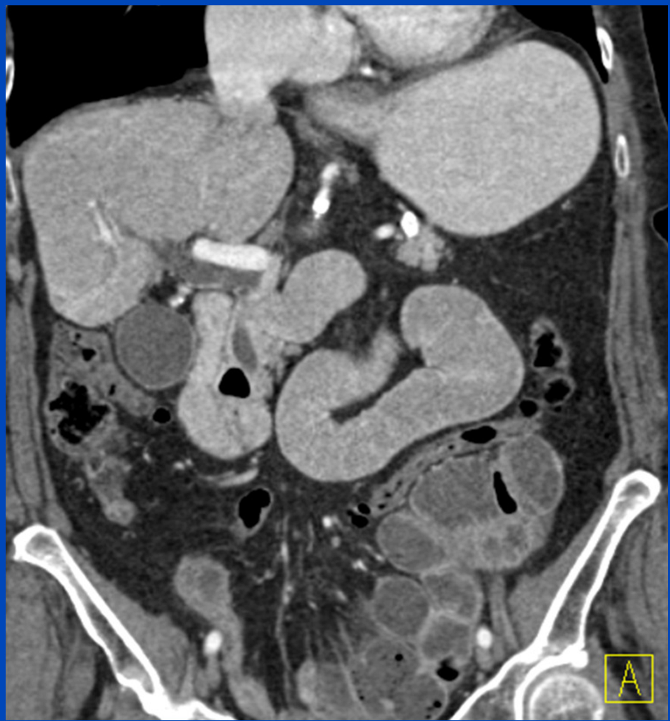


Figure provided by Siemens Healthcare, Forchheim, Germany

Conventional reconstruction

at 100% dose



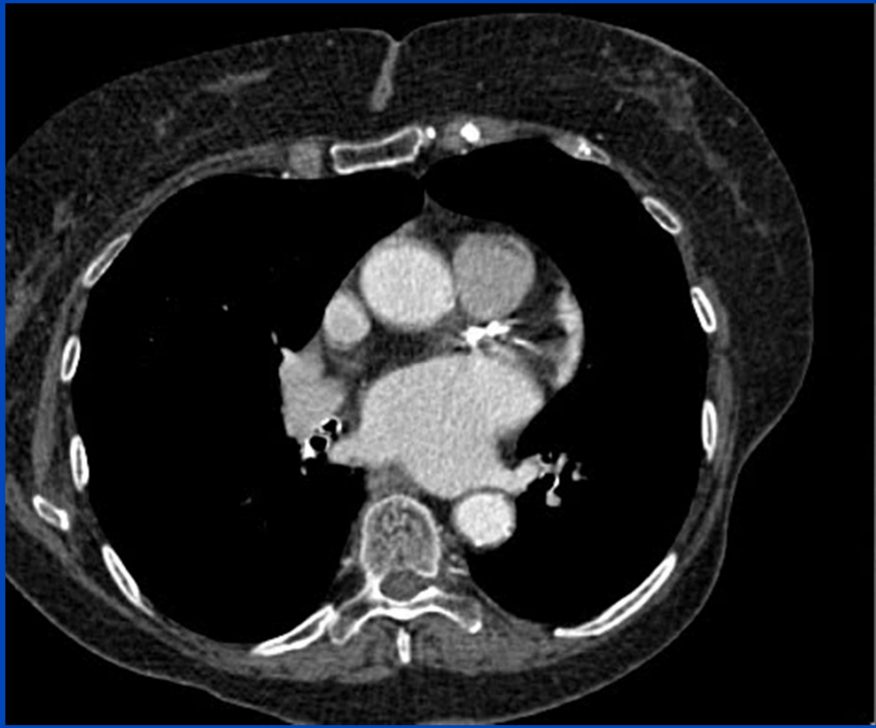
Iterative reconstruction and restoration

at 40% dose

Images provided by Siemens Healthcare, Forchheim, Germany

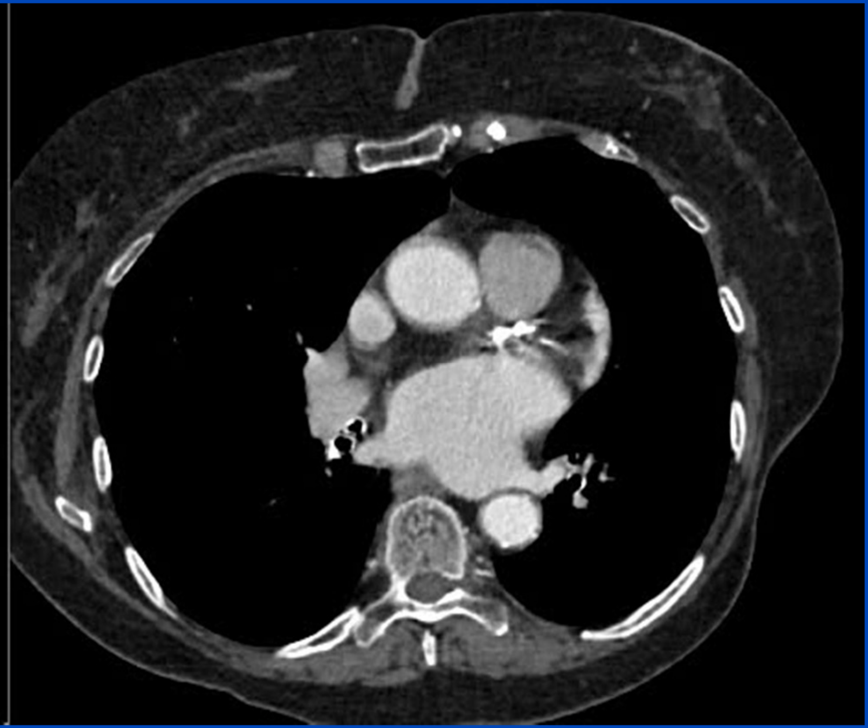
Conventional reconstruction

at 100% dose



Iterative reconstruction and restoration

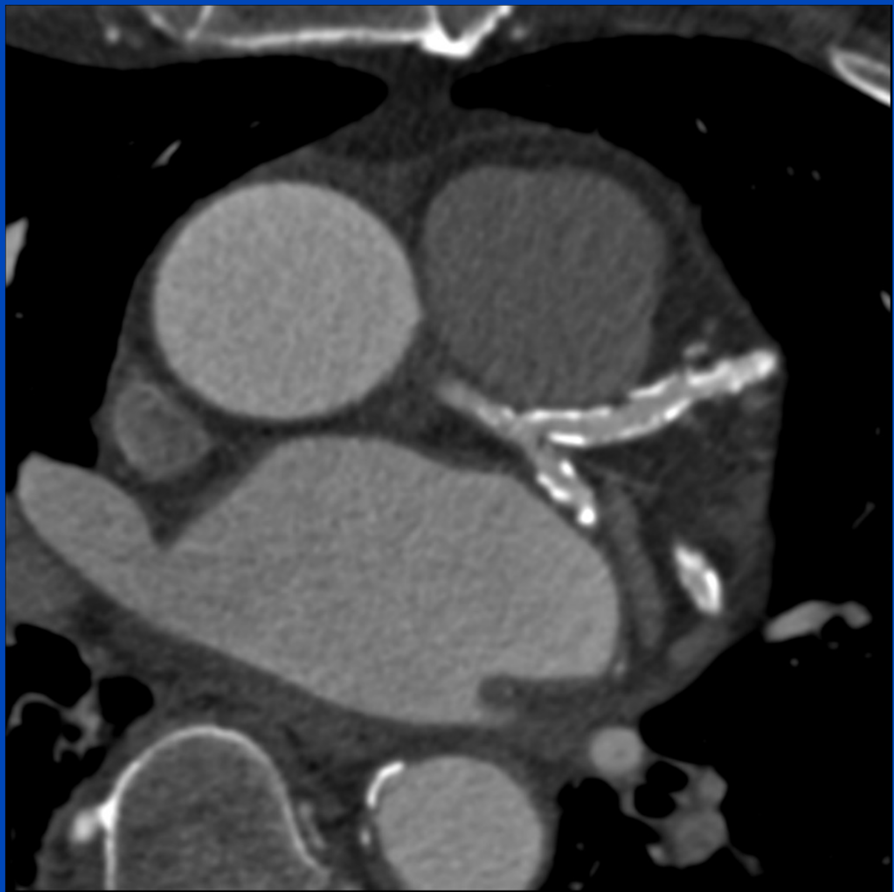
at 40% dose



Images provided by Siemens Healthcare, Forchheim, Germany

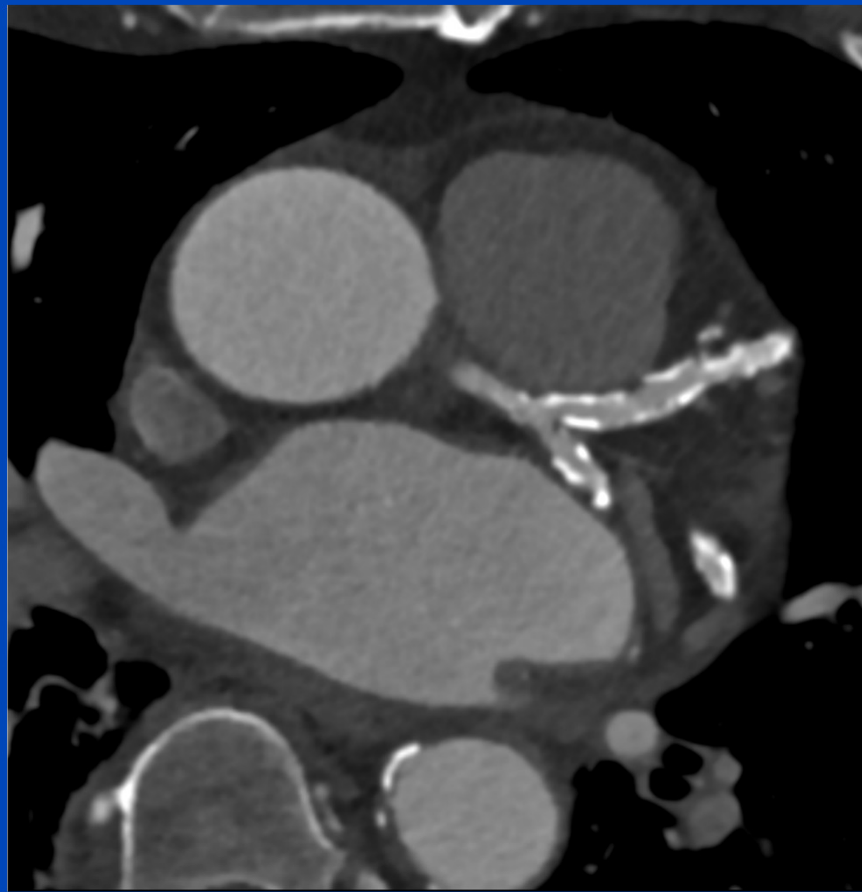
Conventional reconstruction

at 100% dose



Iterative reconstruction and restoration

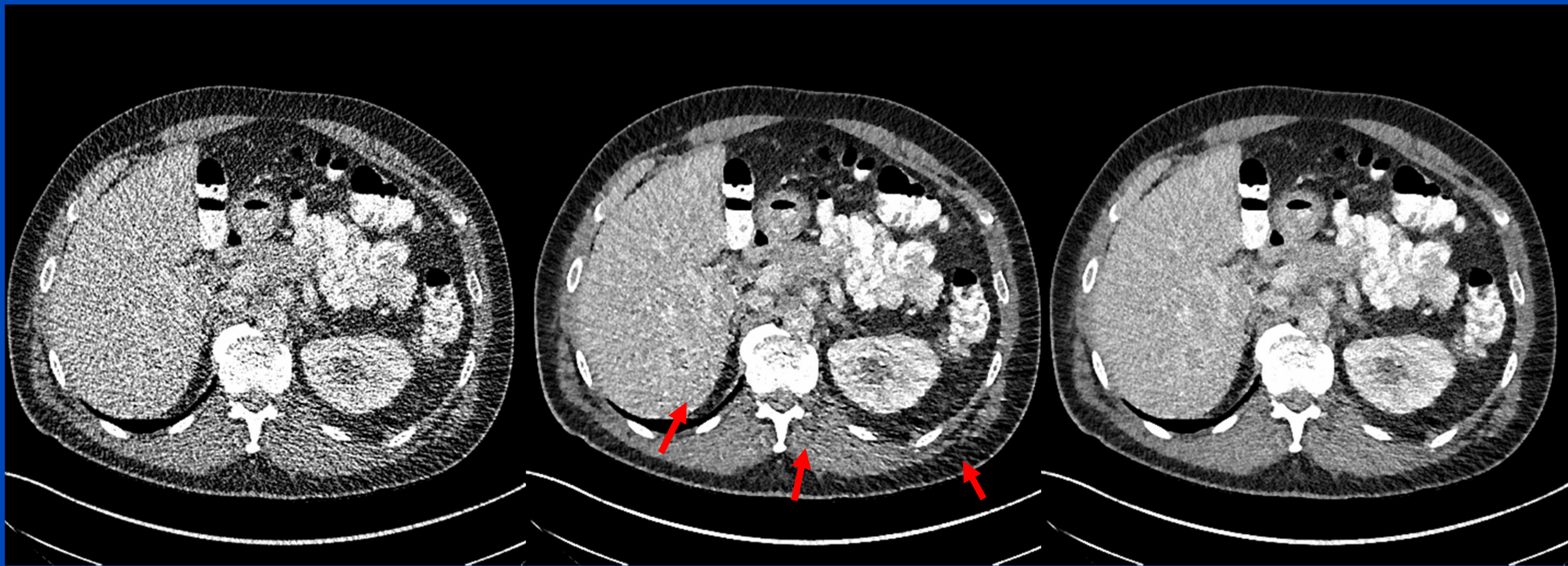
at 40% dose



Images provided by Siemens Healthcare, Forchheim, Germany

dkfz.

Vendor's Improvements in Iterative Reconstruction



Standard
B40

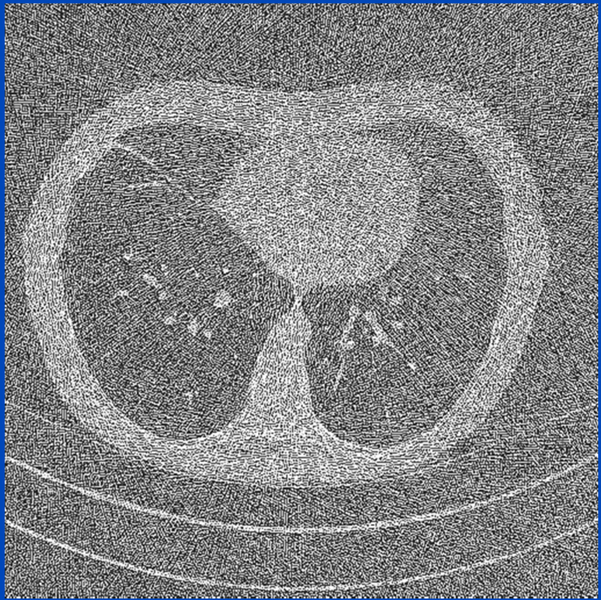
SAFIRE
I40/5

ADMIRE
I40/5

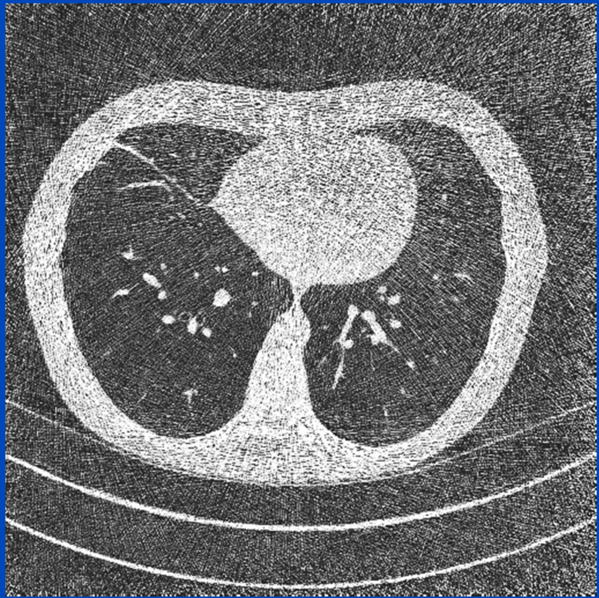
Images provided by Siemens Healthcare, Forchheim, Germany

dkfz.

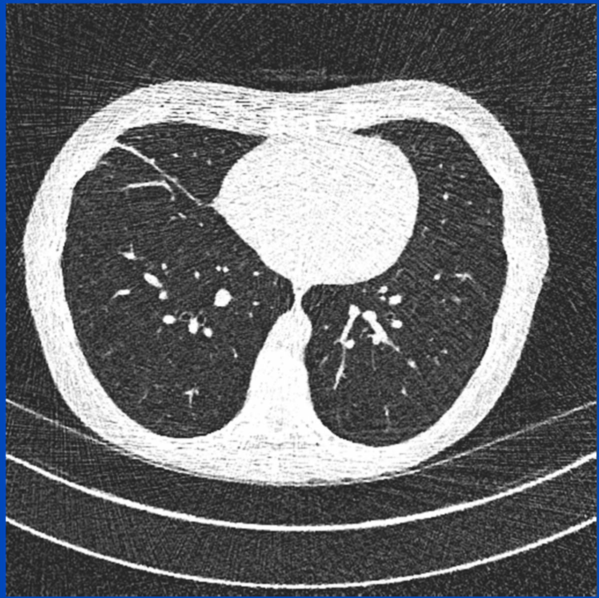
Vendor's Improvements in Iterative Reconstruction



Standard
B64



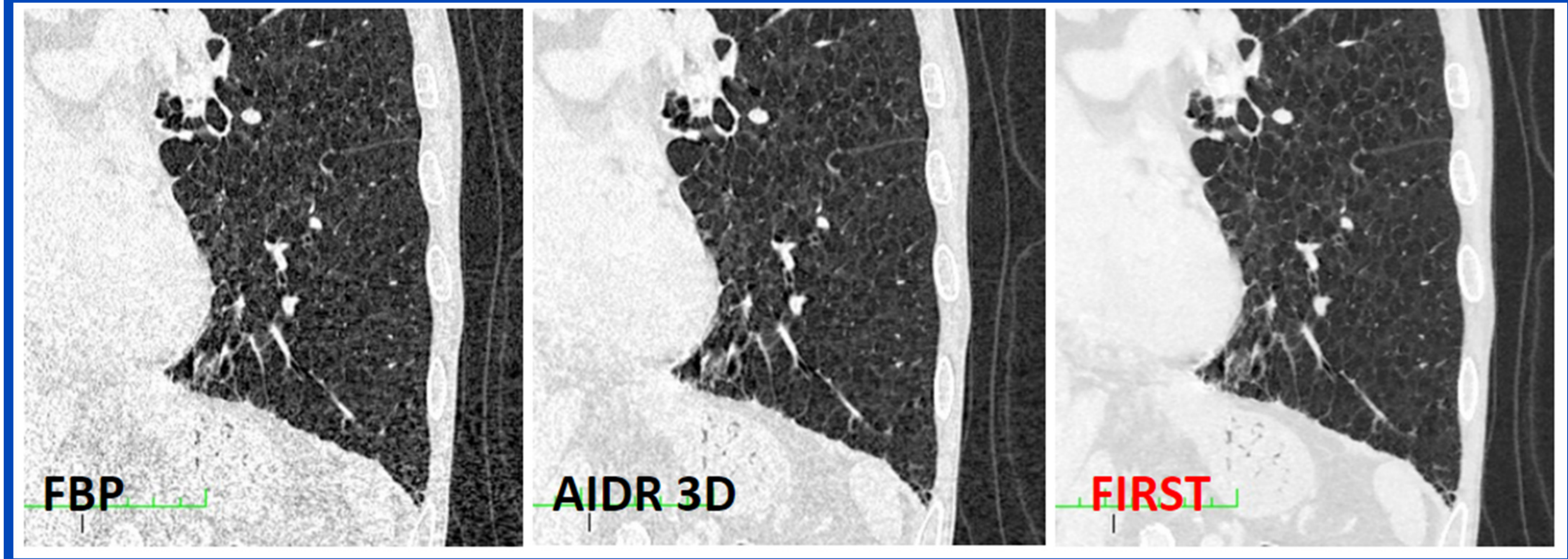
SAFIRE
I64/5



ADMIRE
I64/5

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

Vendor's Improvements in Iterative Reconstruction

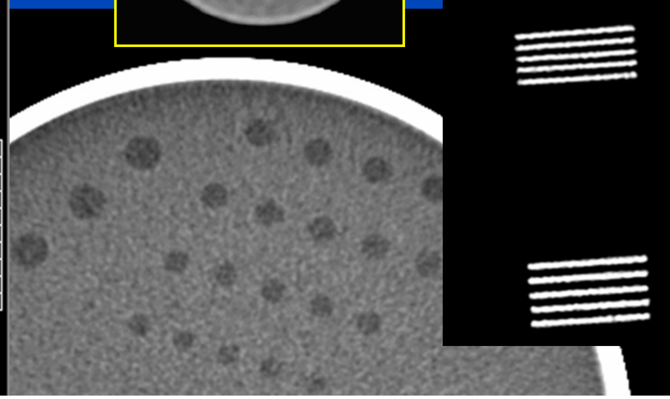


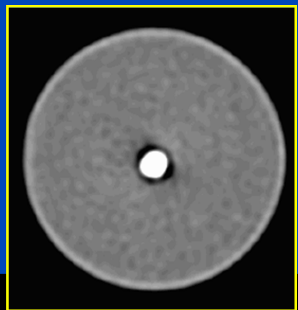
Toshiba Aquilion ONE ViSION FIRST Edition

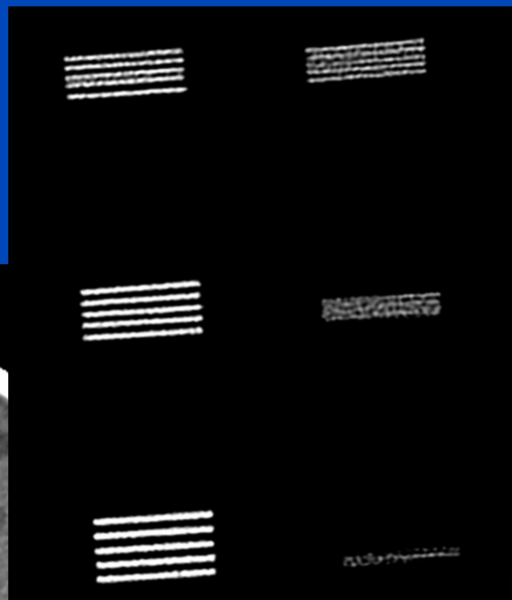
Akagi et al. Full Iterative Reconstruction Optimized for Specific Organs - Principle and Capabilities. RSNA 2015.

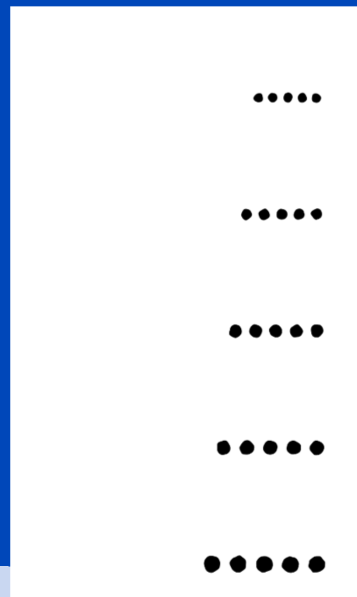
Usual Assumption: CT is Linear and Translation Invariant

- **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**
- **…**



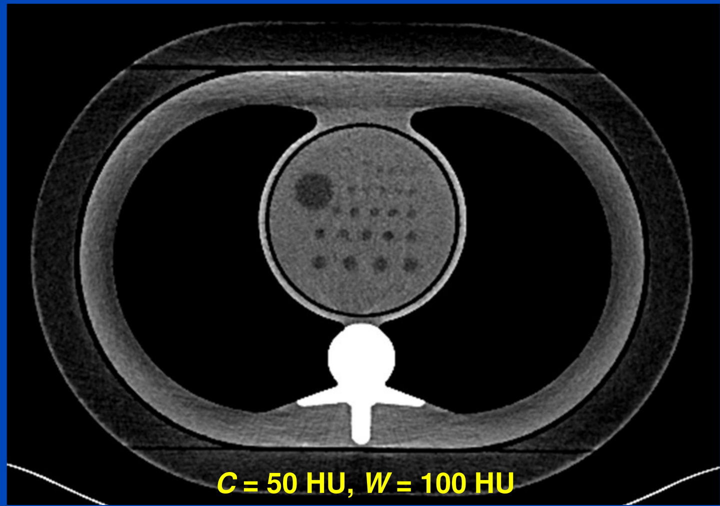


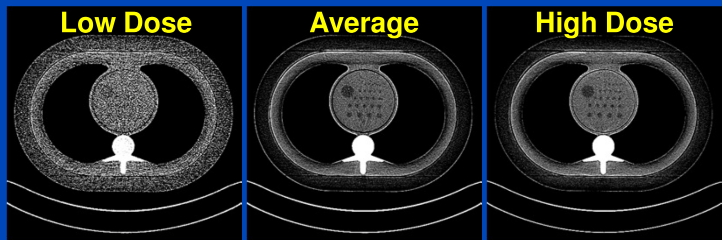




Simple Example 1
(Taken at the Siemens Somatom Flash DSCT Scanner)

- **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**
  - 128 × 0.6 mm collimation
  - 120 kV
  - $p = 0.6$
  - $t_{rot} = 1.0$ s
  - $S_{eff} = 0.6$ mm
  - 1 full 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



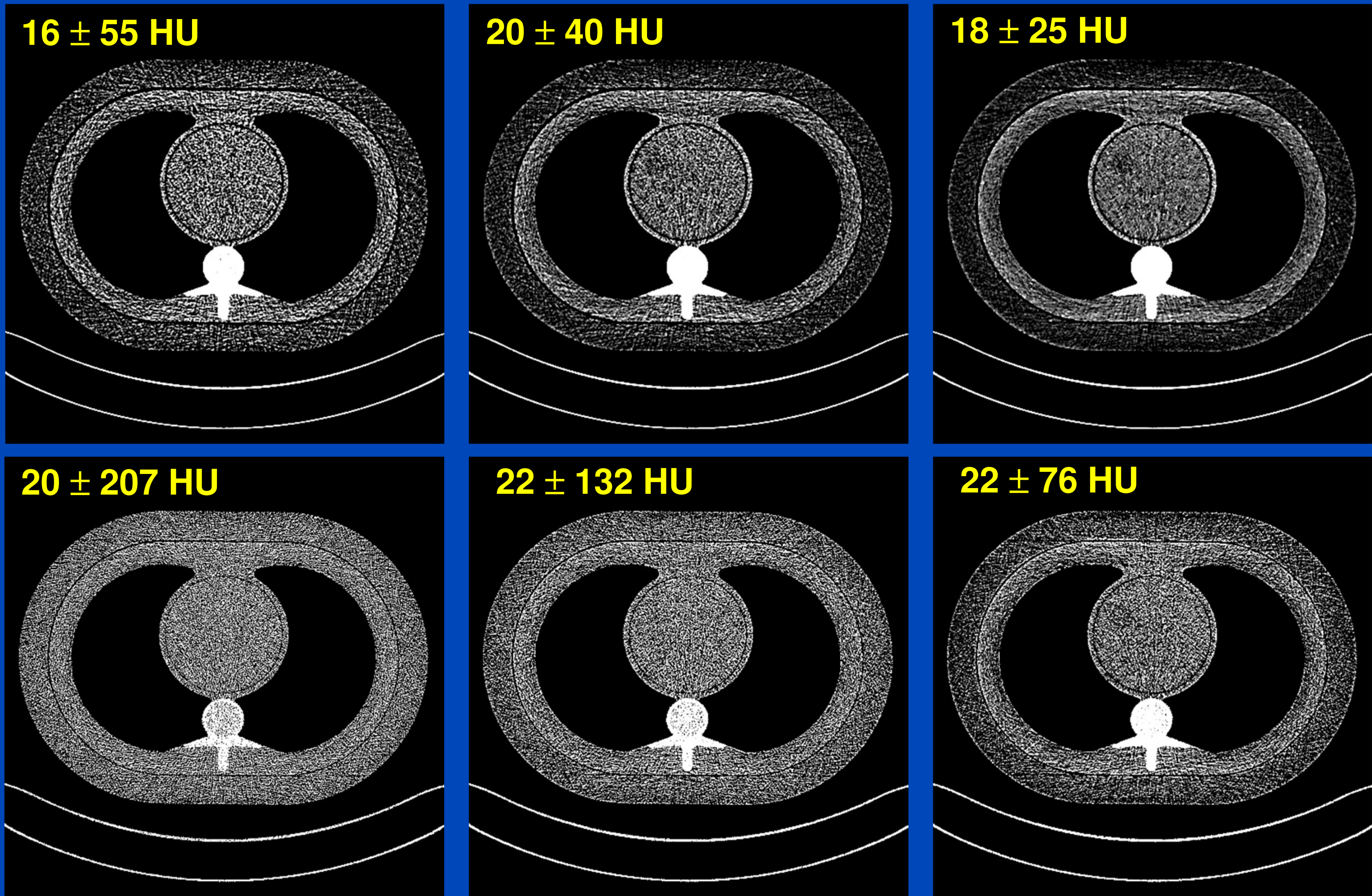


Single Low Dose Scan

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

30s

50s

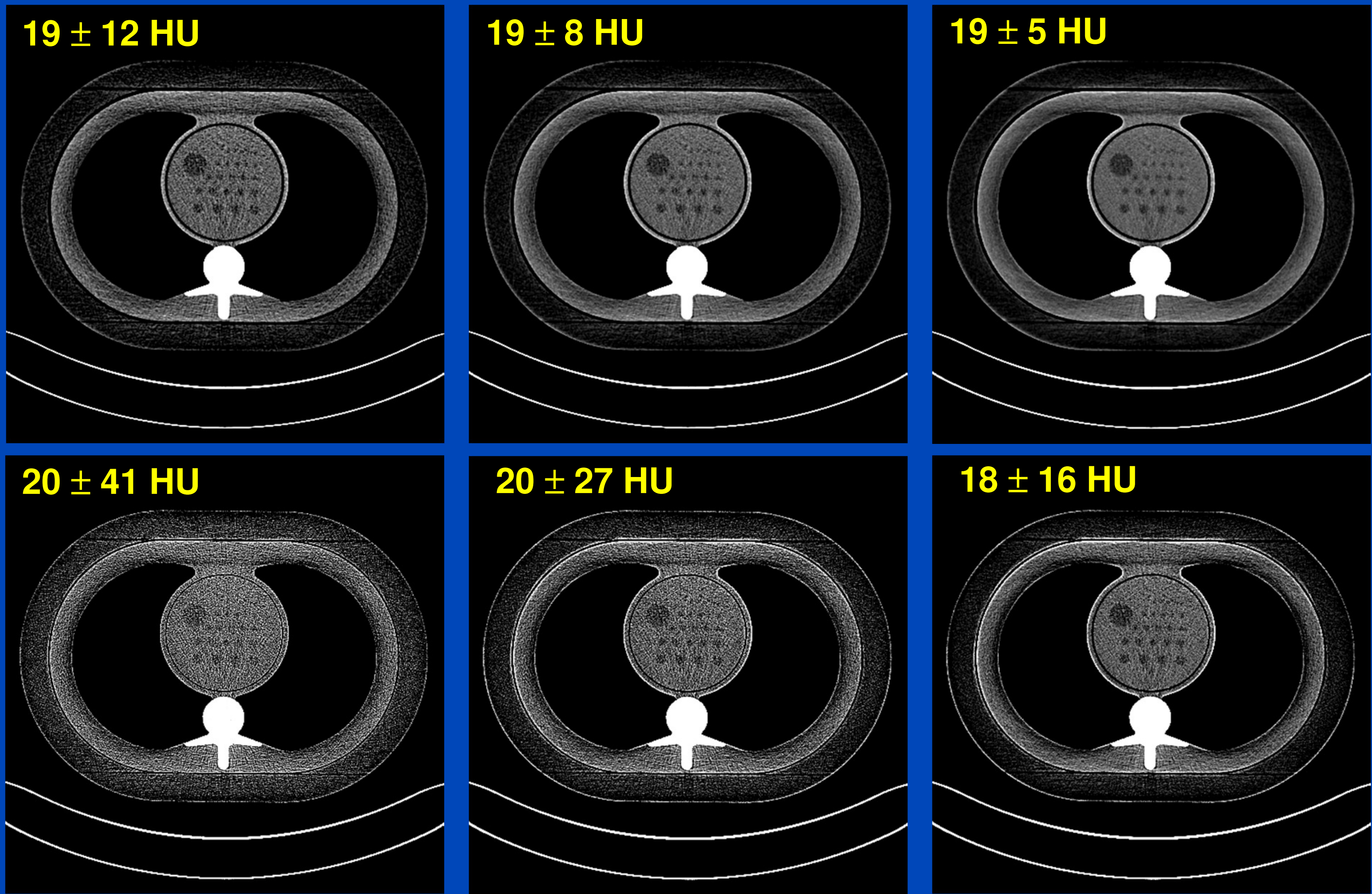


Average of 25 Low Dose Scans

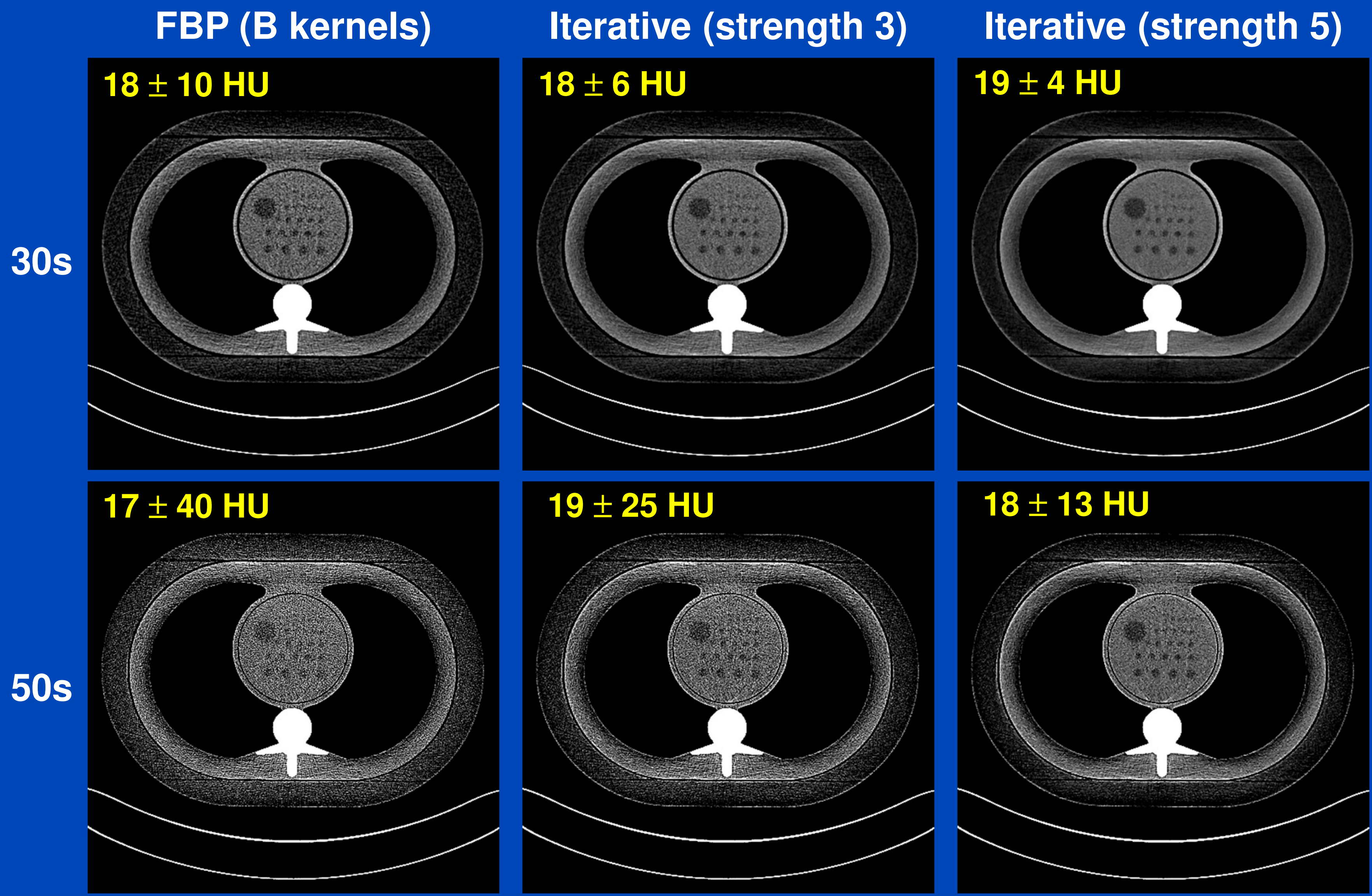
FBP (B kernels) | Iterative (strength 3) | Iterative (strength 5)

30s

50s



High Dose Scan

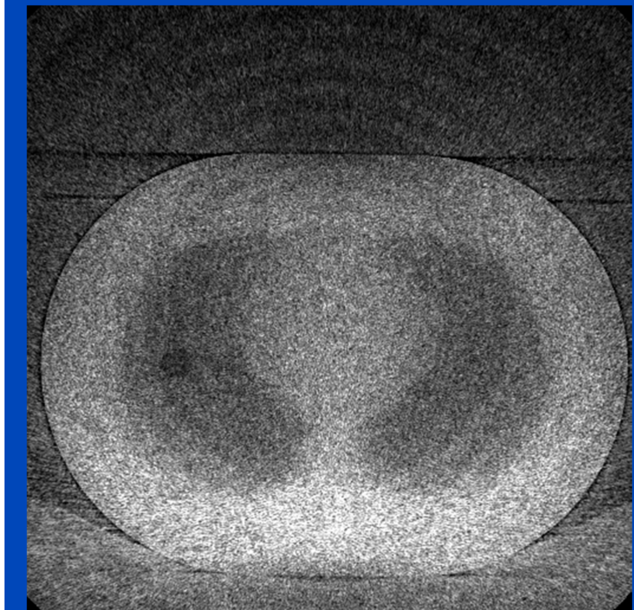


MK1

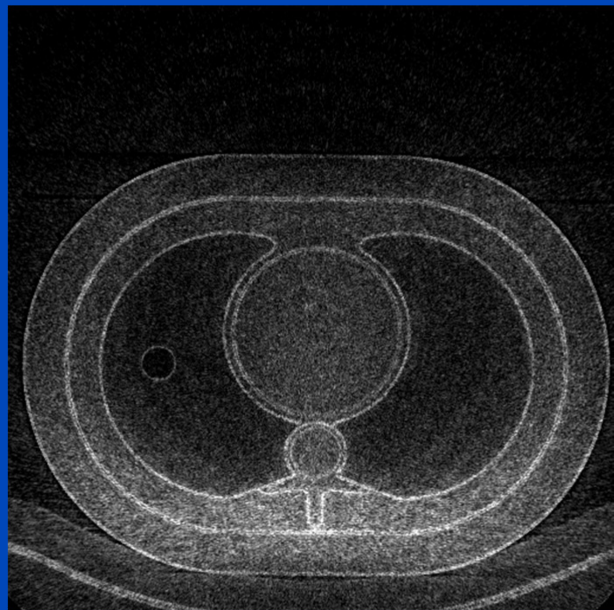
Simple Example 2

- **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**

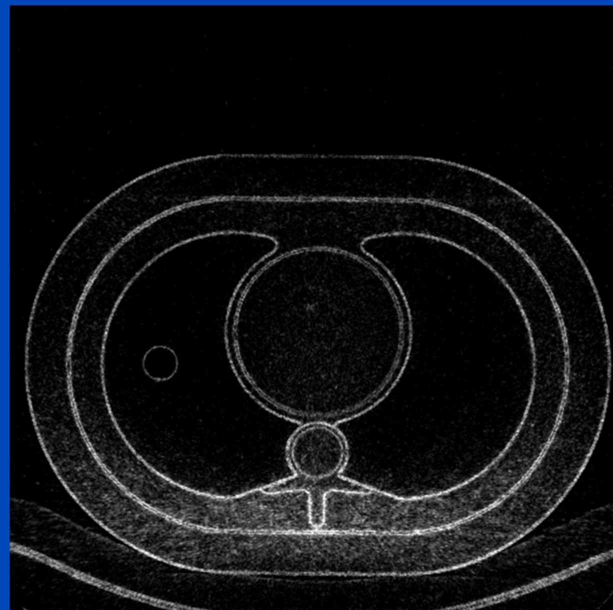
FBP (B30s)



SAFIRE (I30s strength 3)



SAFIRE (I30s strength 5)



C = 40 HU, W = 50 HU

Slide 153

MK1 Anmerkung von Stefan S.: Warum sind bei dem sigma FBP Bild die Kanten außen sichtbar und zur Lunge hin verwischt?

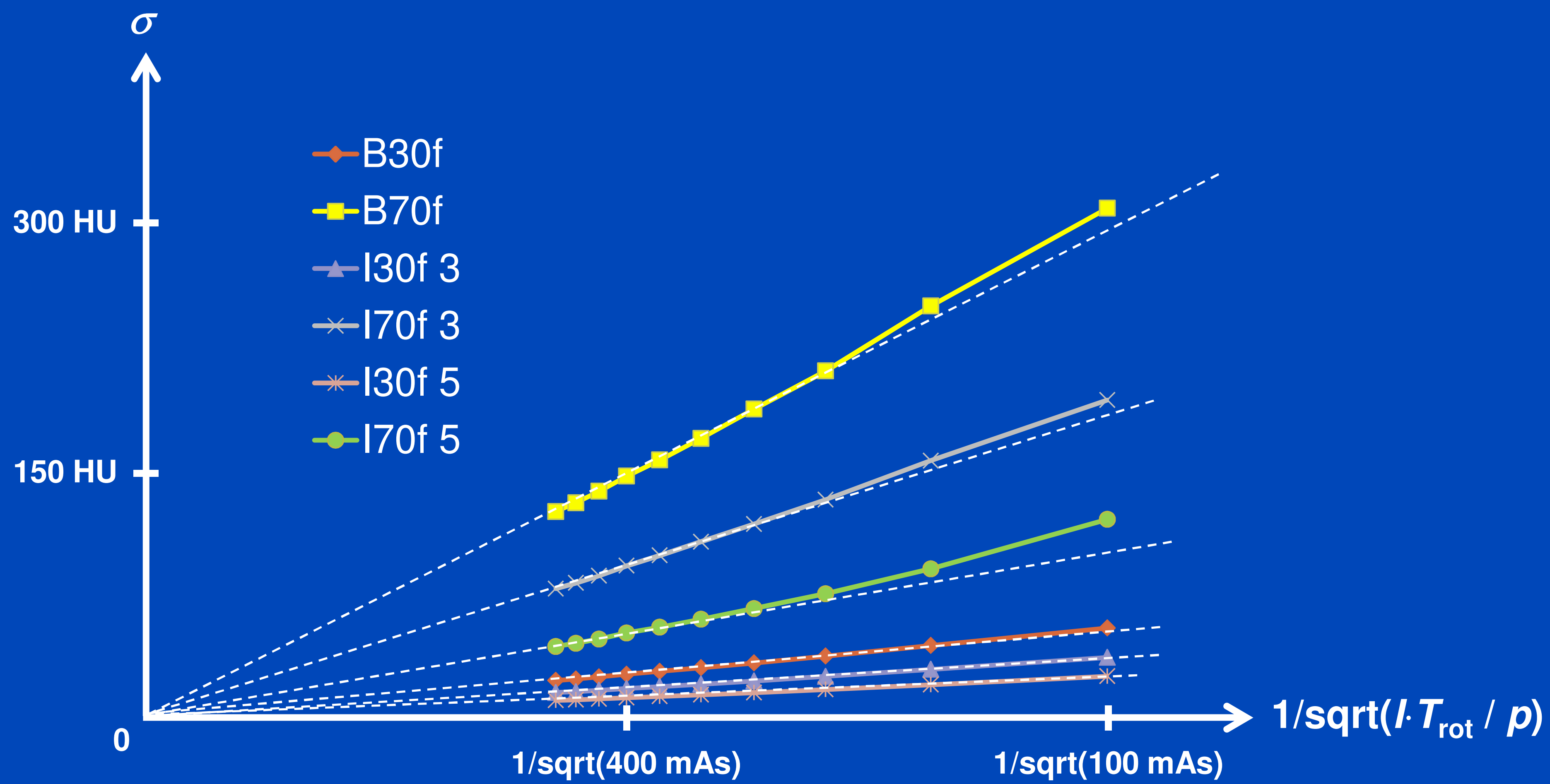
Idee: außen wirkt das Gibbs Phänomen und die CT-Werte werden nach unten hin abgeschnitten (-1024 HU. Die Lunge hat einen CT-Wert von ~ -800 HU, dort wird nichts abgeschnitten)
Prof. Dr. Marc Kachelrieß; 24.06.2015

Simple Example 3

(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.

Conclusions on the Simple Examples and General Comments

- The (SAFIRE) iterative reconstruction
  - reduces noise in low and medium contrast regions
  - reduces spatial resolution in low and medium contrast regions
  - preserves noise in high contrast regions (edges)
  - preserves spatial resolution in high contrast regions (edges)
  - shows the conventional square-root relation of image noise and dose
- Other iterative standard reconstruction algorithms
  - also attempt to reduce noise and preserve resolution
  - will also not reduce noise at edges
  - may behave different in detail
  - may deviate more or less from the square-root behaviour
- Future iterative reconstructions algorithms
  - may compensate for motion
  - may use stronger a priori knowledge (e.g. dictionaries)
  - …

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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Guang-Hong Chen[a)]
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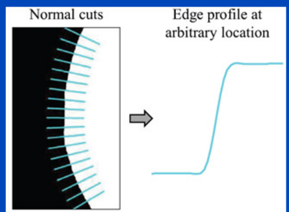
(Received 8 March 2014; revised 9 May 2014; accepted for publication 2 June 2014; published 23 June 2014)

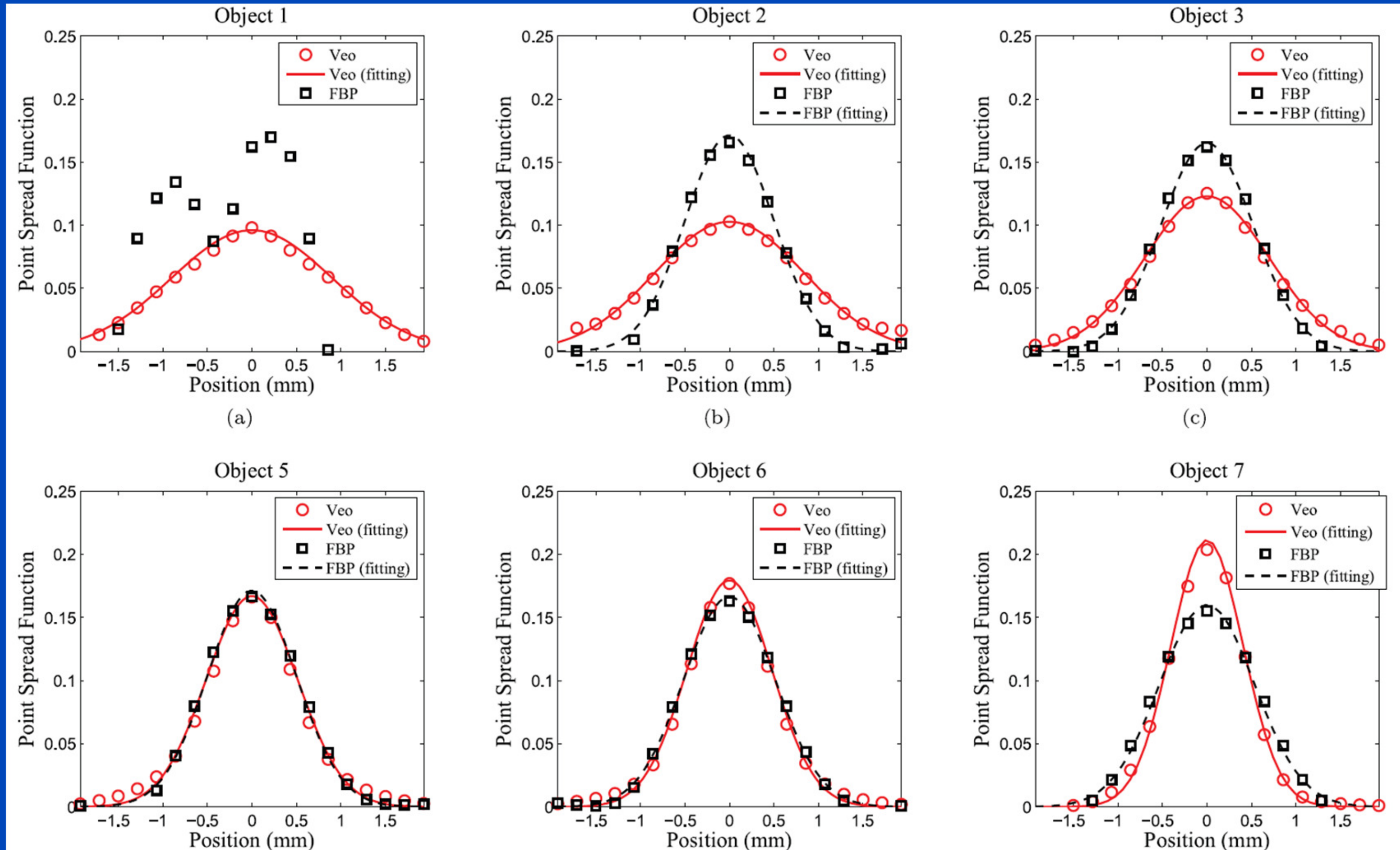
Li et al., MedPhys 41(7), July 2014

Contrast Dependency of the PSF

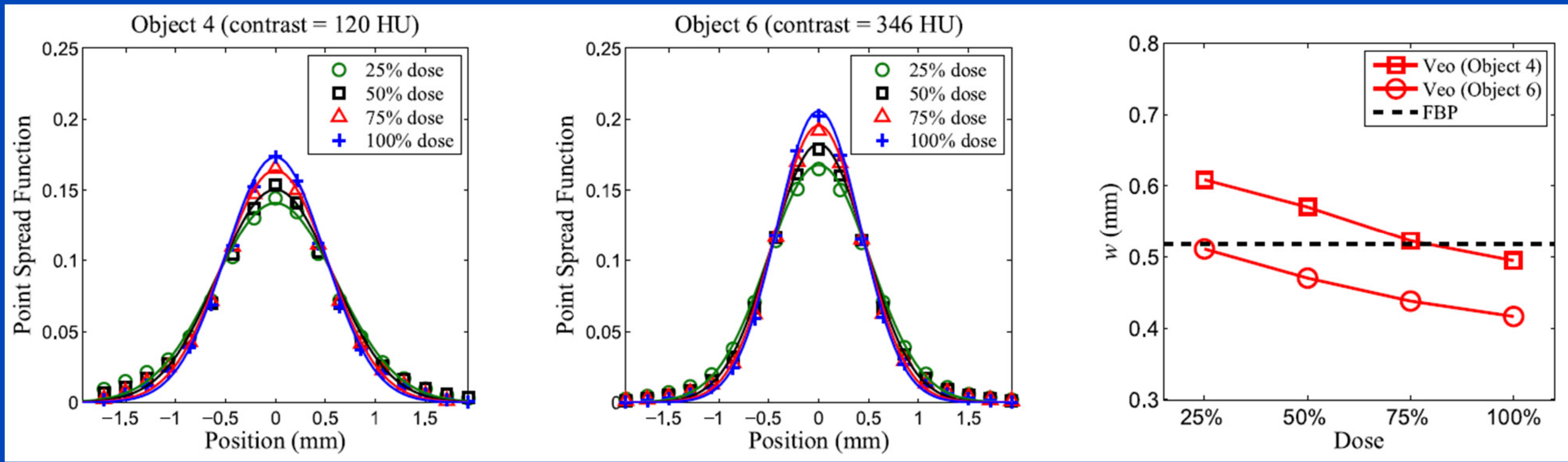
(of GE's FBP and Veo Algorithms)

	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





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
  - ...

Thank You!

The 4th 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.

Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.