Refresher Course RC413, ECR 2020, Vienna, Austria

Updates and Future Perspectives to CT

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DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Part 1: CT Hardware

Canon Aquilion ONE Genesis

GE Revolution Apex

Philips IQon Spectral CT

Siemens Somatom Force

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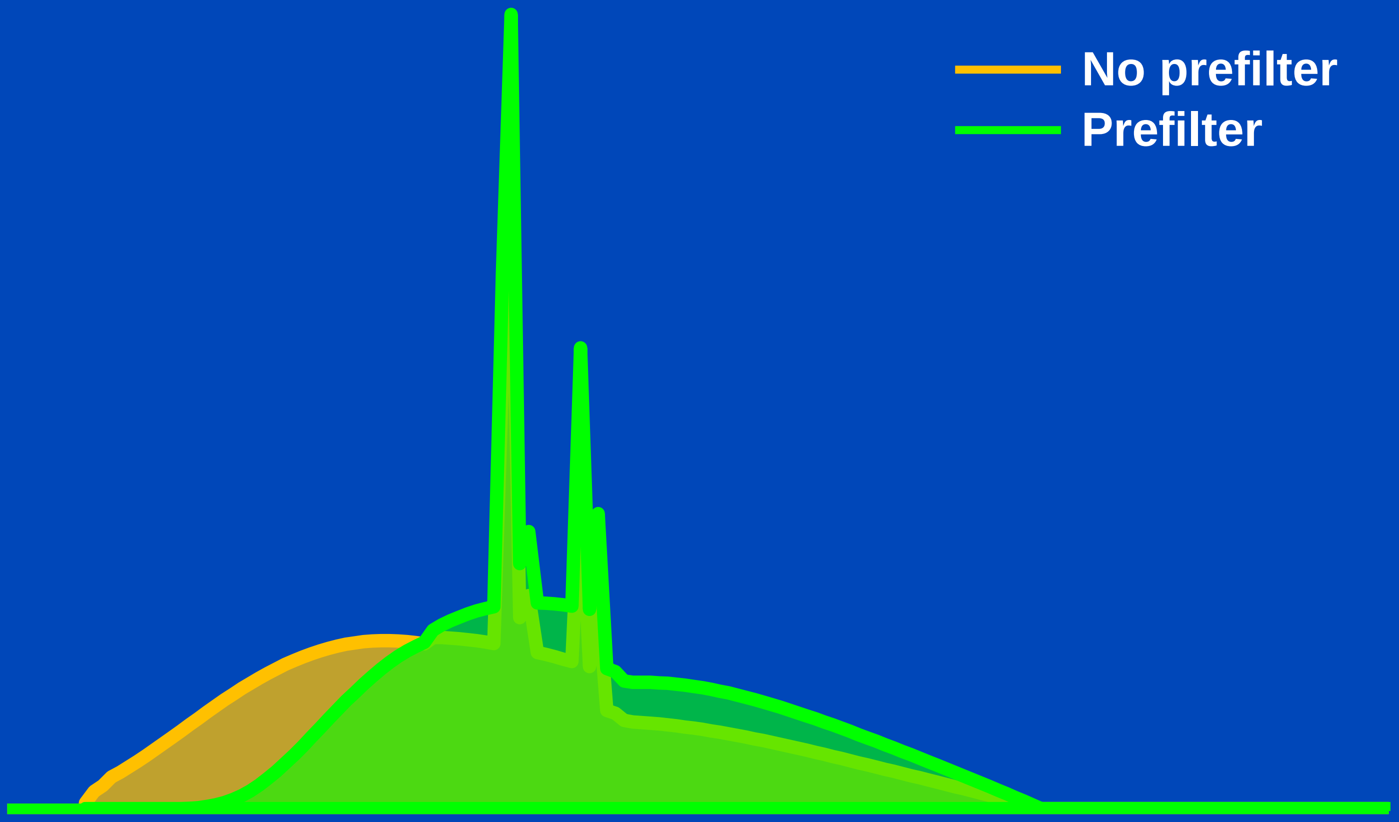
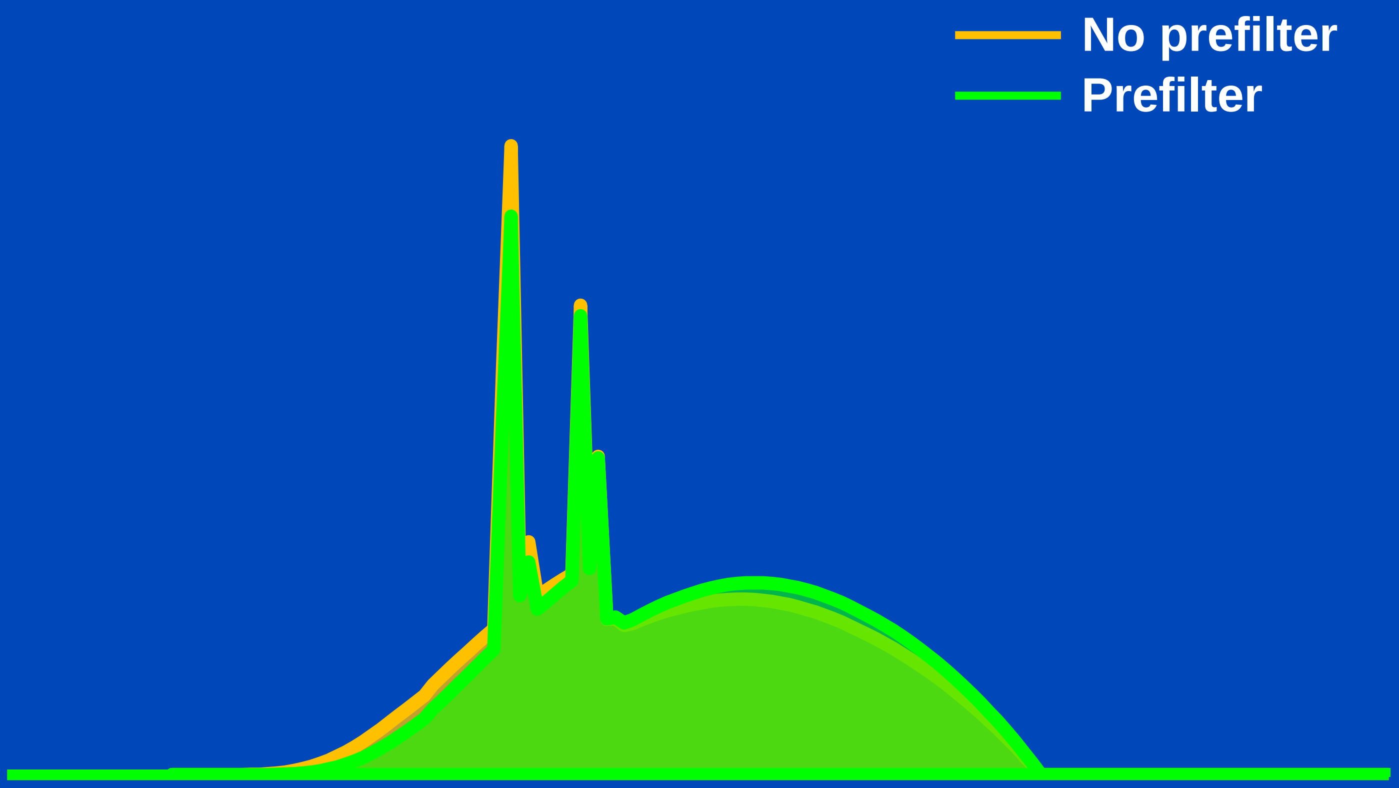
120 kV + 0 mm water with and without prefilter



120 kV + 320 mm water with and without prefilter



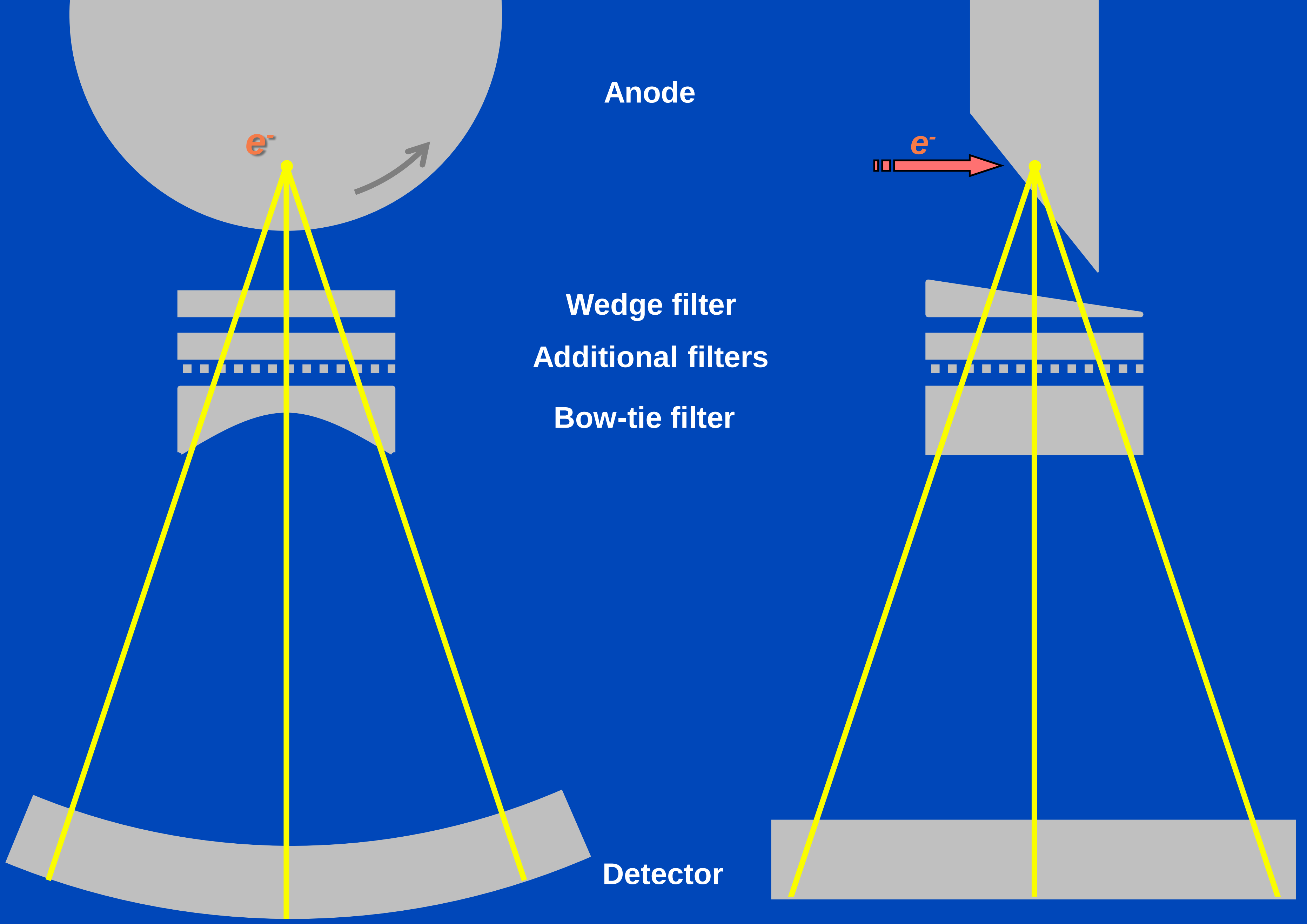


Figure not drawn to scale. Type and order of prefiltration may differ from scanner to scanner.
Depending on the selected protocol filters are changed automatically (e.g. small bowtie for pediatric scans).

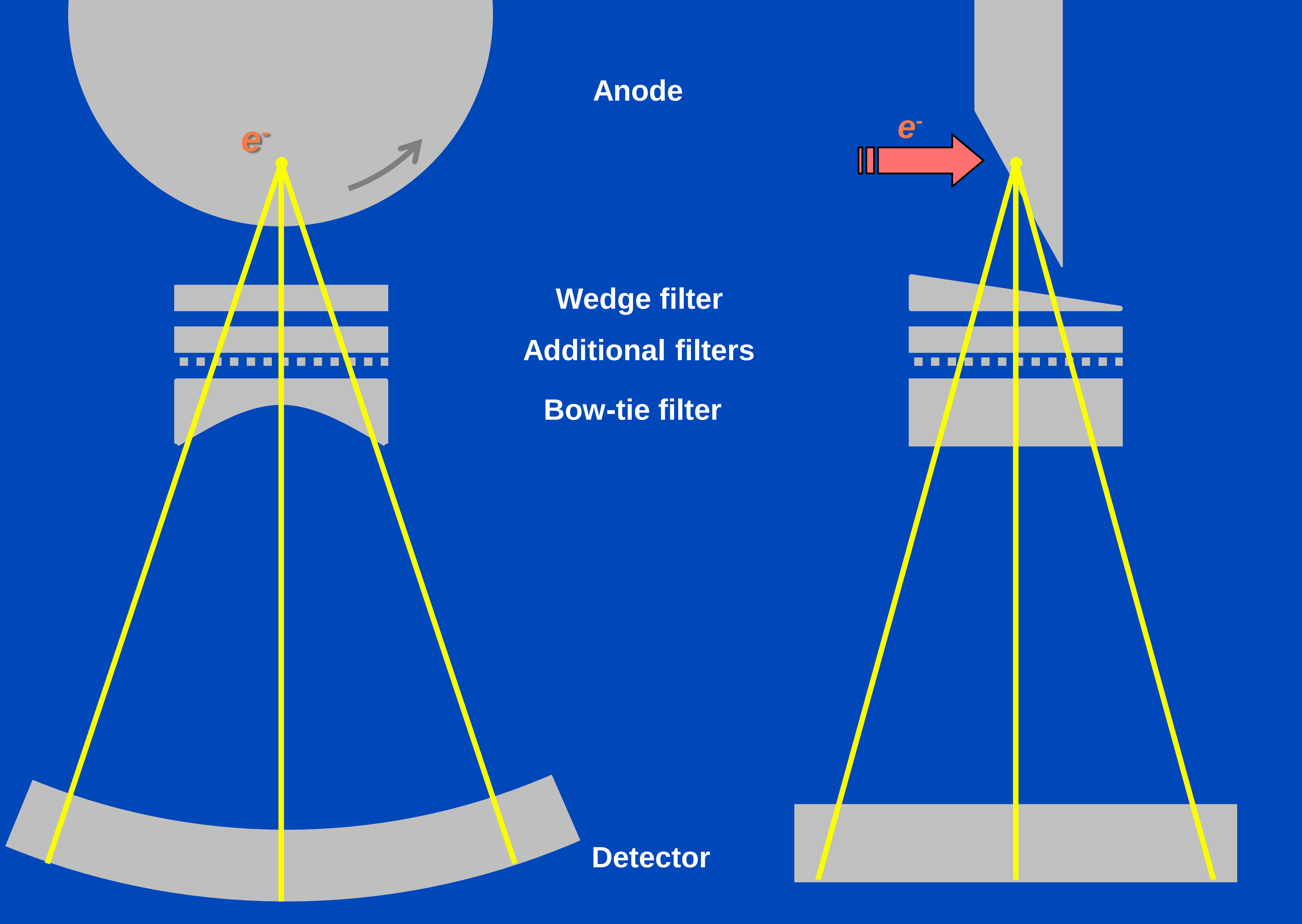


Figure not drawn to scale. Type and order of prefiltration may differ from scanner to scanner.
Depending on the selected protocol filters are changed automatically (e.g. small bowtie for pediatric scans).

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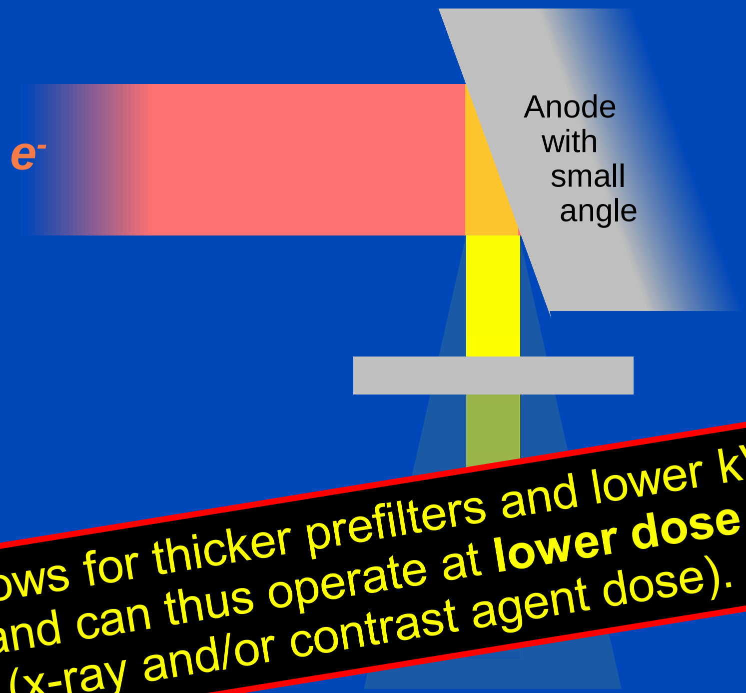
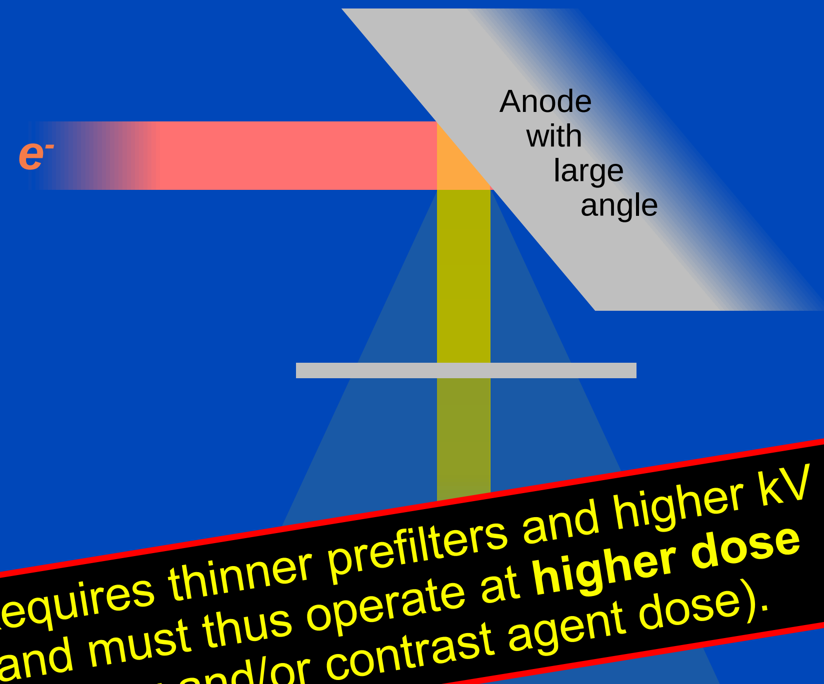
Narrow Cone = High Tube Power

Wide Cone = Low Tube Power



Allows for thicker prefilters and lower kV and can thus operate at **lower dose** (x-ray and/or contrast agent dose).



Requires thinner prefilters and higher kV and must thus operate at **higher dose** (x-ray and/or contrast agent dose).

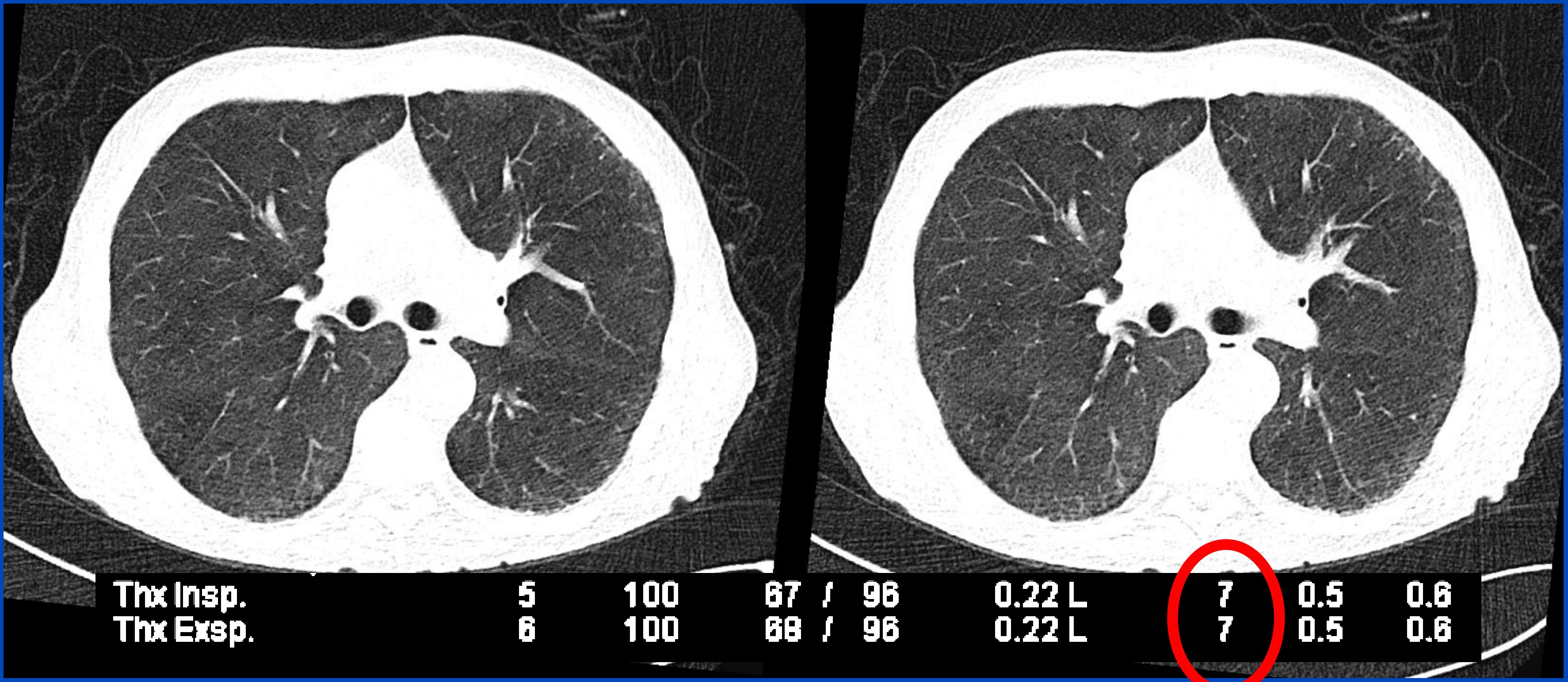
… at the same spatial resolution

Onset of target melting (rule of thumb)[1]: 1 W/µm

[1] D.E. Grider, A. Writh, and P.K. Ausburn. Electron Beam Melting in Microfocus X-Ray Tubes. J. Phys. D: Appl. Phys 19:2281-2292, 1986

Somatom Force: Ultra Low Dose Lung Imaging

- Atypical pneumonia in inspiration and expiration
- Turbo Flash mode, 737 mm/s, 100 kV Sn
- DLP = 7 mGy·cm ≈ 0.1 mSv per scan



Courtesy of University Hospital Mannheim

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Removable Prefilters

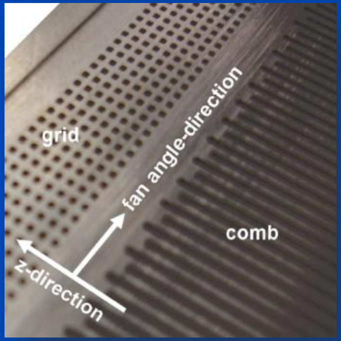
- Thicker prefilters
  - improve the dose efficiency
  - require higher x-ray tube power
- Thus, patient-specific filters are advantageous
  - filter changer
  - filter thicknesses for a variety of patient sizes and anatomical regions
  - tube should operate close to its maximum power
- Systems that use patient-specific filtration today:
  - 0.4 mm Sn for Siemens‘ Somatom Flash, Drive, go.Now, go.Up and go.all
  - 0.6 mm Sn for Siemens‘ Somatom Force, Edge Plus, go.Top and Definition Edge
  - 0.4 mm and 0.7 mm Sn for Siemens‘ Somatom X.cite

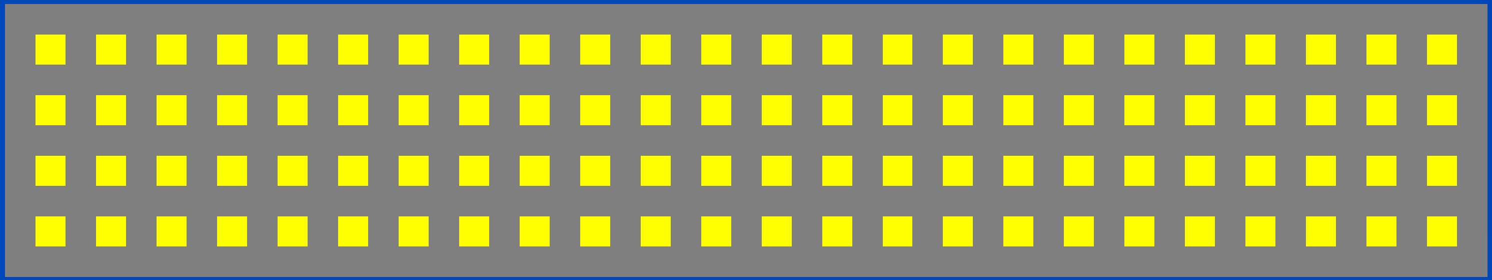
Ultra High Resolution Scans

- **With energy integrating detectors UHR requires[1,2]**
  - **detector comb or detector grid**
  - **αFFS and/or zFFS**
- **Realizations**
  - **Somatom Flash and Force comb (0.61 mm → 0.33 mm)**
  - **Somatom Flash grid (0.61 mm → 0.33 mm and 0.56 mm → 0.53 mm)**
- **Dose loss**
  - **about 50% with comb (46% + penumbra for Flash or Force)**
  - **about 75% with grid (66% + penumbra for Flash)**
- **Dose penalty**
  - **about two-fold dose needed with comb**
  - **about three-fold dose needed with grid**

Flash (0.7 mm × 0.8 mm focus)
- UHR: 1D comb
- zUHR: 2D grid

Force (0.4 mm × 0.5 mm focus)
- UHR: 1D comb
- sUHR: 1D comb + z-deconv





[1]Flohr et al. Novel ultrahigh resolution data acquisition and image reconstruction for multi-detector row CT. Med. Phys. 34(5):1712-1723, May 2007.
[2]Meyer et al. Initial results of a new generation DSCT system using only an in-plane comb filter for UHR temporal bone imaging. Eur Radiol 25:178-185, 2015.

Ultra High Resolution Scans

- **Canon offers the Aquilion Precision a system with dedicated ultra high resolution pixels**
  - **0.25 mm pixel size at iso**
  - **50% less septa thickness**
  - **1792 channels**
  - **160 detector rows**
  - **1D anti scatter grid**
  - **0.4 × 0.5 mm focal spot**
  - **10800 rpm anode, liquid metal bearing**
  - **512, 1024 or 2048 pixels per image**
  - **No need for comb or grid: small pixel effect becomes relevant (see below)**

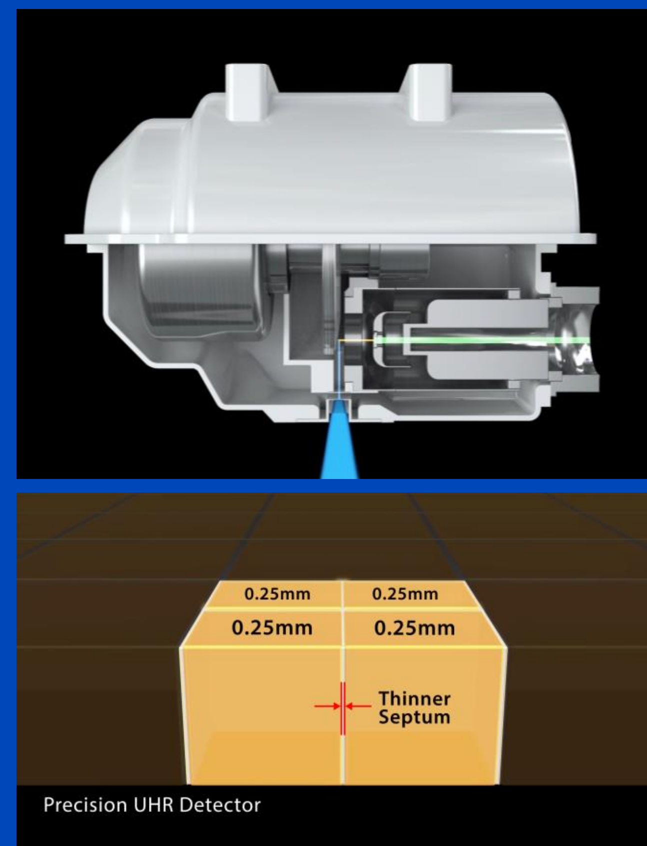
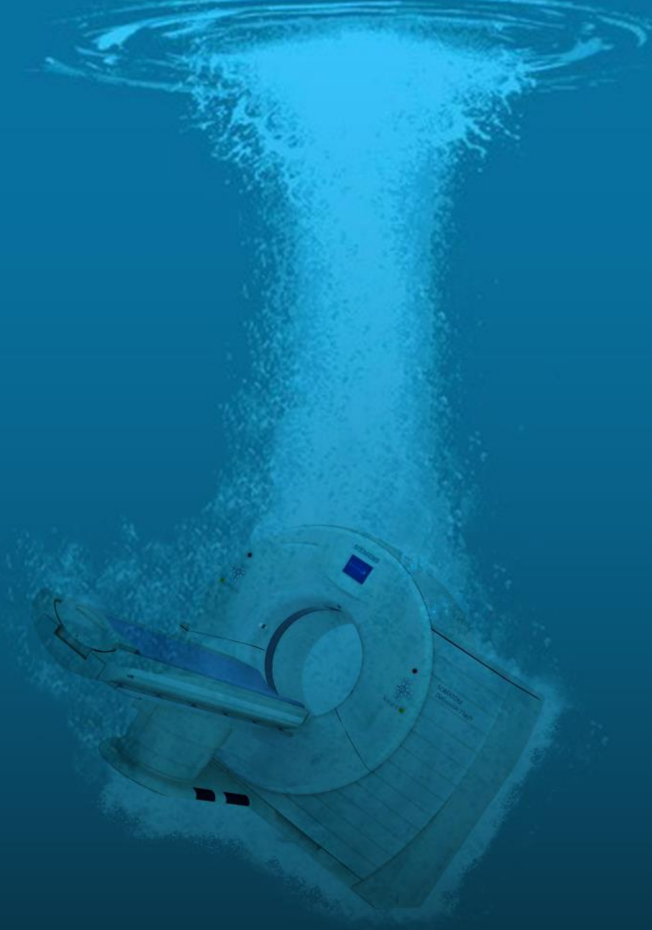


Image courtesy of Canon

Premium CT Systems 2019/2020

Vendor	CT-System	Configuration	Collim, Cone	Rotation, FOM	Max. Power, Anode Angle	Max. mA @ low kV, patient-specific filters	Matrix	DECT
Canon	Aquilion ONE Genesis	320 × 0.5 mm PUREViSION	160 mm, 15°	0.275 s, 50 cm	100 kW, 10° MegaCool Vi	600 mA @ 80 kV, none	512	2 scans
Canon	Aquilion Precision	160 × 0.25 mm PUREViSION	40 mm, 3.9°	0.35 s, 50 cm	72 kW, 7° MegaCool	600 mA @ 80 kV, none	512, 1024, 2048	2 scans
GE	Revolution Apex	256 × 0.625 mm GemStone Clarity	160 mm, 15°	0.28 s, 50 cm	108 kW, 10° Quantix 160	1300 mA @ 70+80 kV, none	512	fast TVS or 2 scans
GE	CardioGraphe	192 × 0.73 mm (focused FOM)	140 mm, 17°	0.24 s, 25 cm	72 kW, 13° Dual MCS-2093	600 mA @ 80 kV, none	512	2 scans
Philips	Brilliance iCT	2 · 128 × 0.625 mm NanoPanel 3D	80 mm, 7.7°	0.27 s, 50 cm	120 kW, 8° iMRC	925 mA @ 80 kV, none	512, 768, 1024	2 scans
Philips	IQon	2 · 64 × 0.625 mm NanoPanel Prism	40 mm, 3.9°	0.27 s, 50 cm	120 kW, 8° iMRC	925 mA @ 80 kV, none	512, 768, 1024	sandwich
Siemens	Somatom X.cite	2 · 64 × 0.6 mm Stellar	38.4 mm, 3.7°	0.3 s, 50 cm	105 kW, 8° Vectron	1200 mA @ 70+80+90 kV, {0, 0.4, 0.7} mm Sn	512, 768, 1024	split filter or 2 scans
Siemens	Somatom Force	2 · 2 · 96 × 0.6 mm Stellar	57.6 mm, 5.5°	0.25 s, 50/36 cm	2 · 120 kW, 8° Vectron	2 · 1300 mA @ 70+80+90 kV, {0, 0.6} mm Sn	512, 768, 1024	DSCT
Siemens experimental	Somatom CounT	32×0.5/24×0.25 mm (photon counting)	16 mm, 1.5°	0.5 s, 50/28 cm	77 kW, 7° Straton MX P	500 mA @ 70 kV {0, 0.4} mm Sn	512, 768, 1024, 2048	4 bin PC

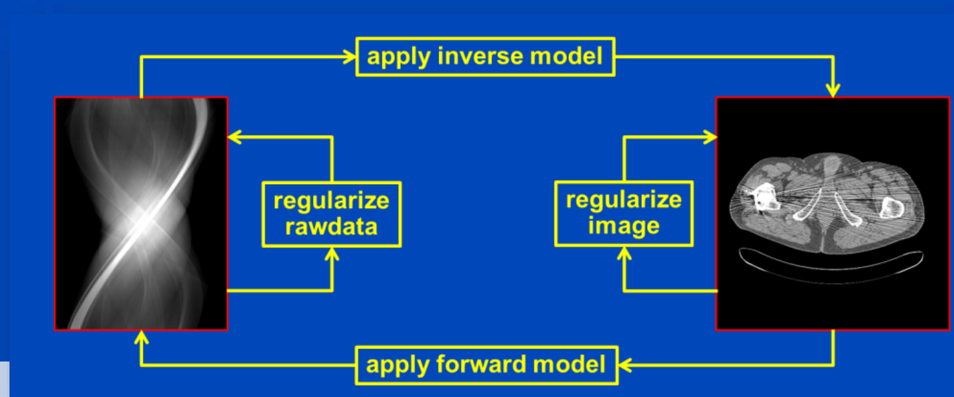


Part 2: Deep Image Formation Software

Premium Recon Algorithms 2019/2020

Vendor	Algorithm	Additional parameters	Sinogram restoration	Image restoration	Full iterations	Deep learning
all	FBP	-	✓	-	-	-
Canon	AIDR-3D enhanced FIRST AiCE	Body, Bone, Brain, Cardiac, Lung each with Mild, Standard, or Strong	✓ ✓ ?	✓ ✓ ✓	- ✓ -	- - ✓
GE	ASIR, ASIR-V True Fidelity	0 – 100% (e.g. ASIR 30%) ???	✓ ?	✓ ✓	- -	- ✓
Philips	iDose IMR	Levels 1 – 7 Soft, Routine, or SharpPlus	✓ ?	✓ ?	- ?	- -
Siemens	IRIS SAFIRE ADMIRE	Strength 1 – 5 Strength 1 – 5 Strength 1 – 5	✓ ✓ ✓	✓ ✓ ✓	- ✓ ✓	- - -

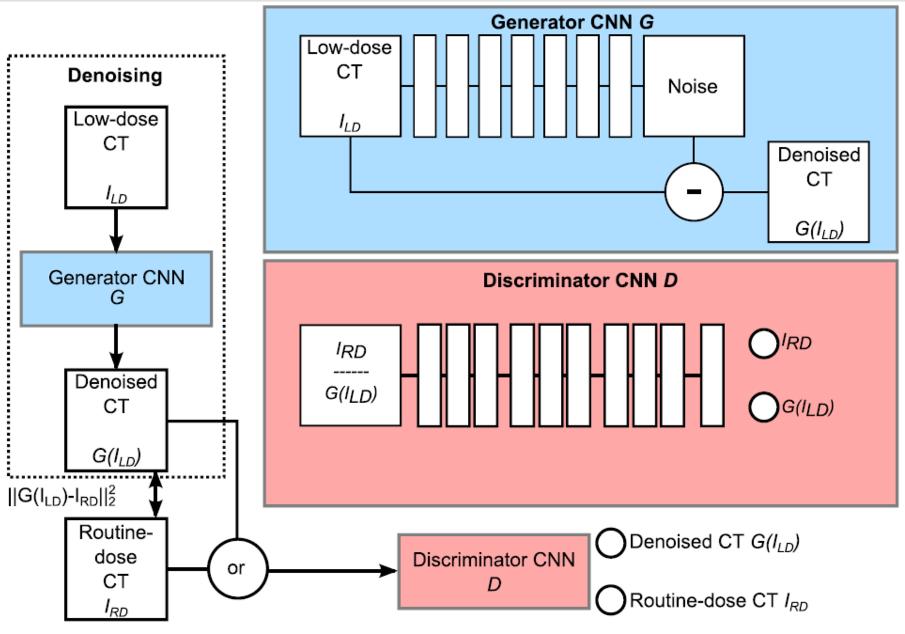
= deep learning-based image restoration so far



dkfz.

Noise Removal Example 1

- Task: Reduce noise from low dose CT images.
- A conditional generative adversarial networks (GAN) is used
- Generator *G*:
  - 3D CNN that operates on small cardiac CT sub volumes
  - Seven 3×3×3 convolutional layers yielding a receptive field of 15×15×15 voxels for each destination voxel
  - Depths (features) from 32 to 128
  - Batch norm only in the hidden layers
  - Subtracting skip connection
- Discriminator *D*:
  - Sees either routine dose image or a generator-denoised low dose image
  - Two 3×3×3 layers followed by several 3×3 layers with varying strides
  - Feedback from *D* prevents smoothing.
- Training:
  - Unenhanced (why?) patient data acquired with Philips Briliance iCT 256 at 120 kV.
  - Two scans (why?) per patient, one with 0.2 mSv and one with 0.9 mSv effective dose.



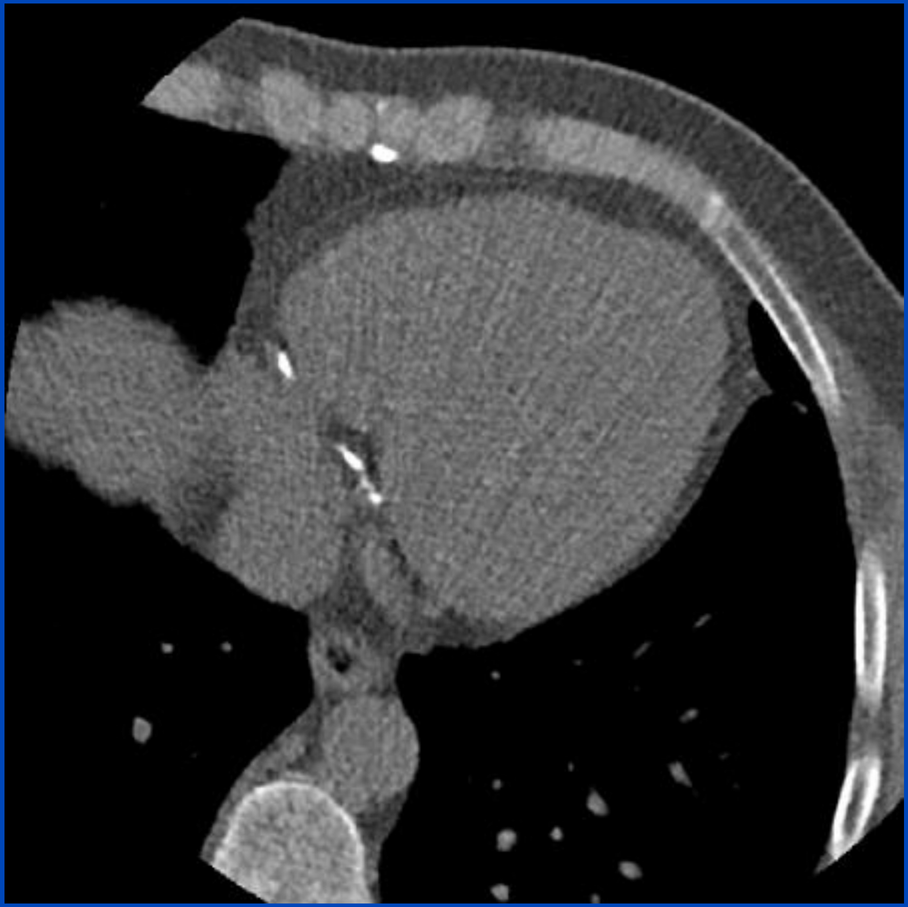
J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 1

Low dose image (0.2 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 1



iDose level 3 reconstruction (0.2 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

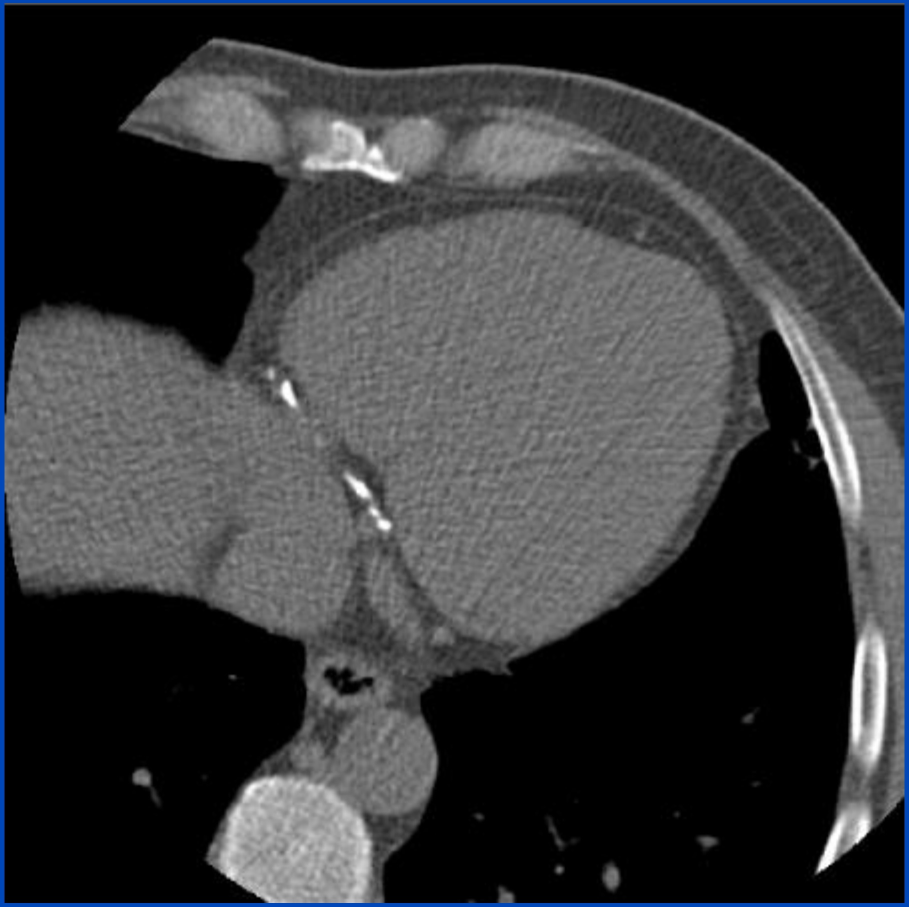
Noise Removal Example 1

Denoised low dose image (0.2 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

dkfz.

Noise Removal Example 1

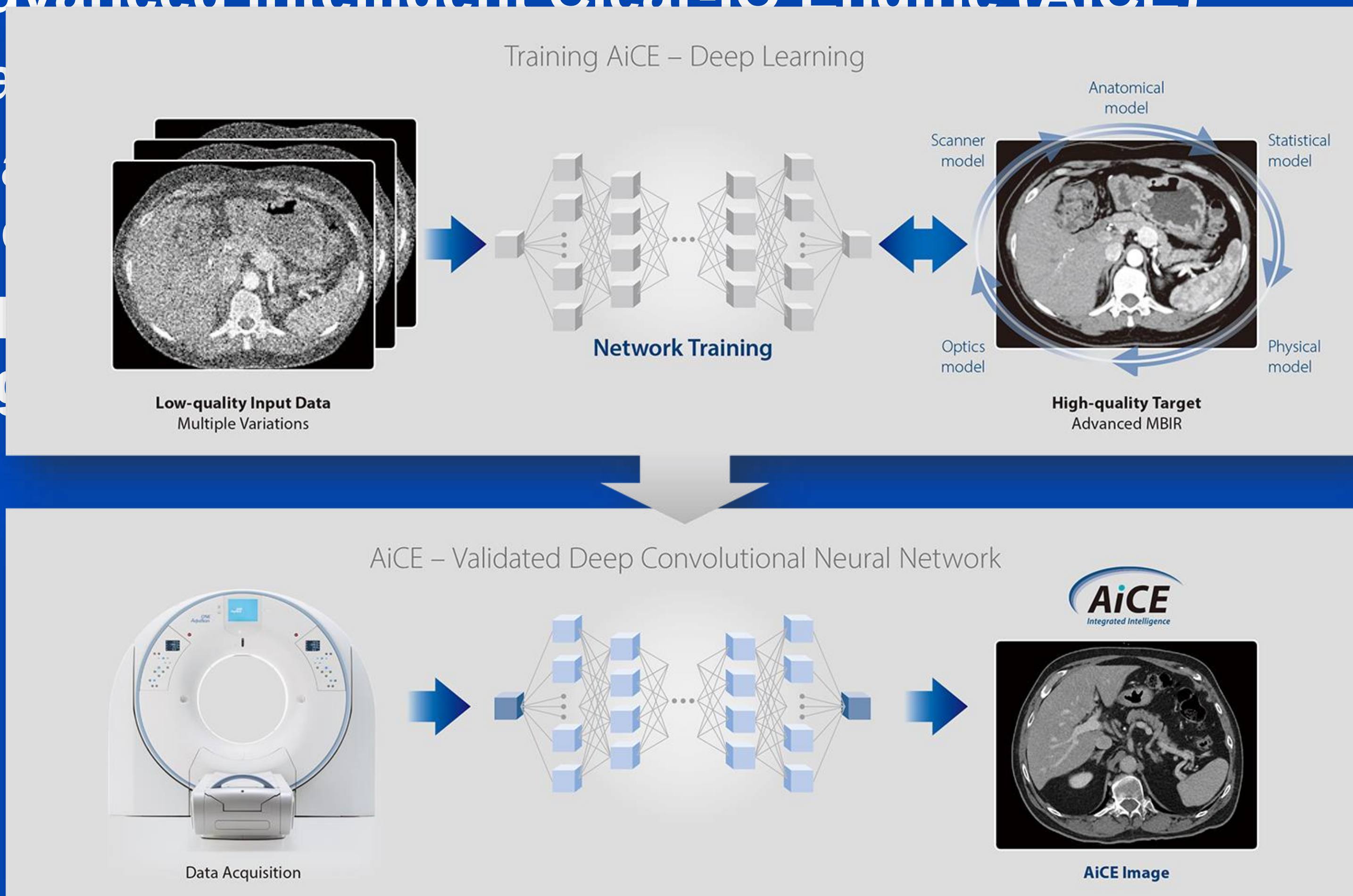


Normal dose image (0.9 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

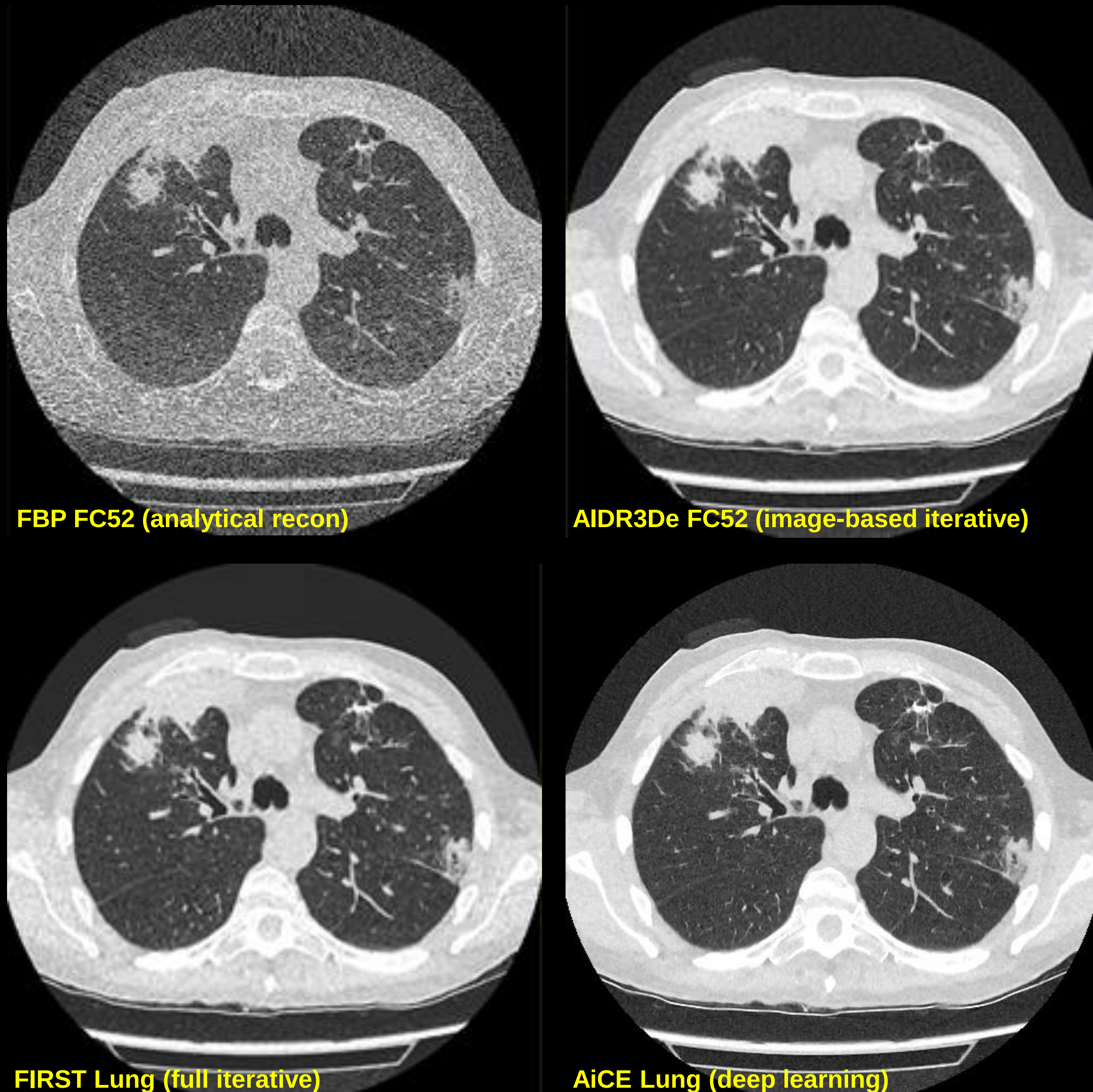
Noise Removal Example 2
Canon's AiCE

- Advanced intelligent Clear-IQ Engine (AiCE)
- Ba
- Tr
  pr .
- FI n a
  hig



Information taken from https://global.medical.canon/products/computed-tomography/aice_dlr

U = 100 kV
CTDI = 0.6 mGy
DLP = 24.7 mGy·cm
D_{eff} = 0.35 mSv



Courtesy of
Radboudumc,
the Netherlands

Noise Removal Example 3
GE's True Fidelity

- Based on a deep CNN
- Trained to restore low-dose CT data to match the properties of Veo, the model-based IR of GE.
- No information can be obtained in how the training is conducted for the product implementation.

2.5D DEEP LEARNING FOR CT IMAGE RECONSTRUCTION USING A MULTI-GPU IMPLEMENTATION

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Jean-Baptiste Thibault [‡], *Charles A. Bouman*[⋆]

[⋆] Electrical and Computer Engineering at Purdue University
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[‡] GE Healthcare
[⊕] Electrical Engineering at University of Notre Dame

ABSTRACT

While Model Based Iterative Reconstruction (MBIR) of CT scans has been shown to have better image quality than Filtered Back Projection (FBP), its use has been limited by its high computational cost. More recently, deep convolutional neural networks (CNN) have shown great promise in both denoising and reconstruction applications. In this research, we propose a fast reconstruction algorithm, which we call Deep

streaking artifacts caused by sparse projection views in CT images [8]. More recently, Ye, et al. [9] developed method for incorporating CNN denoisers into MBIR reconstruction as advanced prior models using the Plug-and-Play framework [10, 11].

In this paper, we propose a fast reconstruction algorithm, which we call Deep Learning MBIR (DL-MBIR), for approximately achieving the improved quality of MBIR using a deep residual neural network. The DL-MBIR method is trained to

FBP

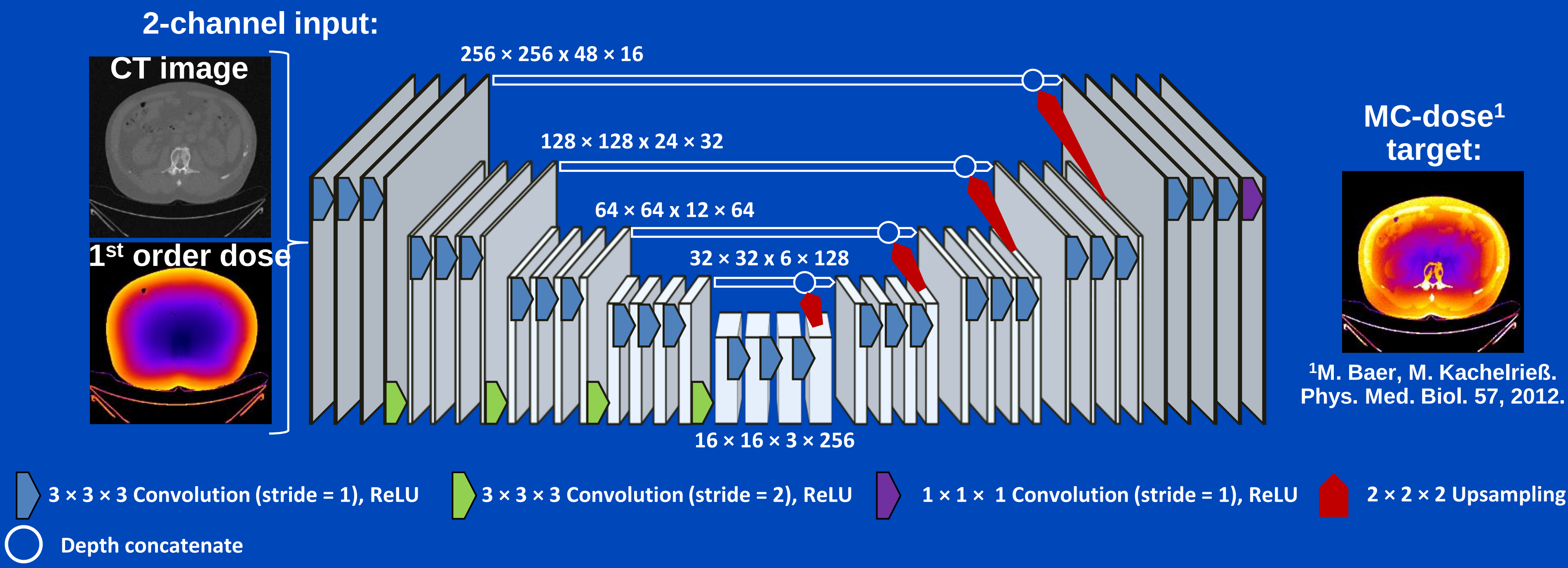
ASIR V 50%

True Fidelity

Courtesy of GE Healthcare

Deep Dose Estimation (DDE)

- **Combine fast and accurate CT dose estimation using a deep convolutional neural network.**
- **Train the network to reproduce MC dose estimates given the CT image and a first-order dose estimate.**



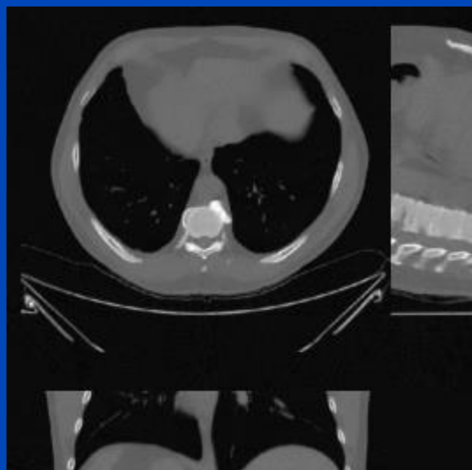
[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 2012.

J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

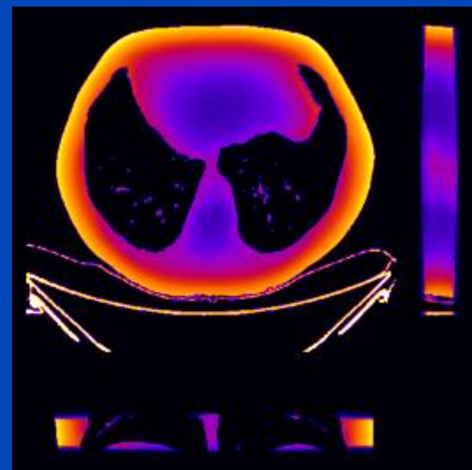
Deep Dose Estimation (DDE)

Thorax, tube A, 120 kV, no bowtie

CT image



First order dose

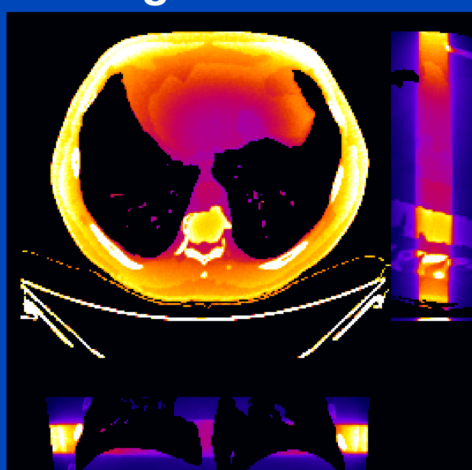


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

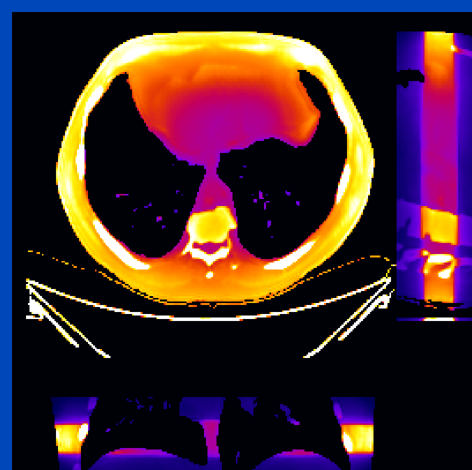
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

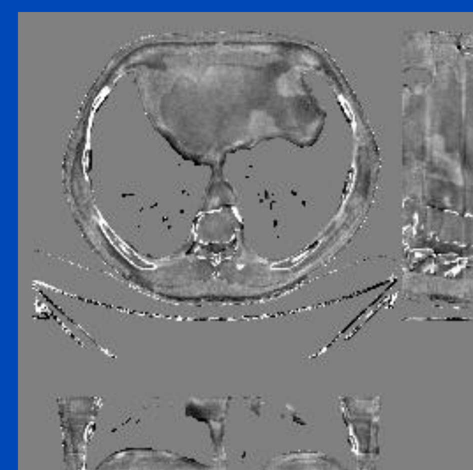
MC ground truth



DDE



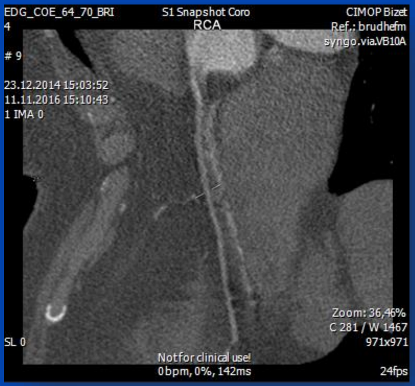
Relative error



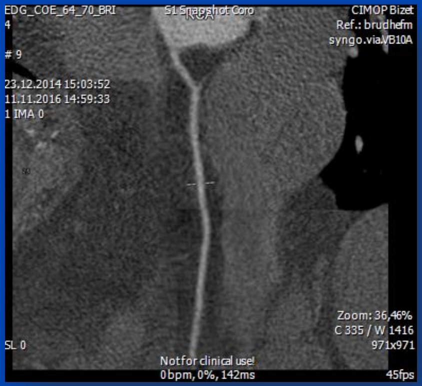
C = 0%
W = 40%

J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

Deep Cardiac Motion Compensation

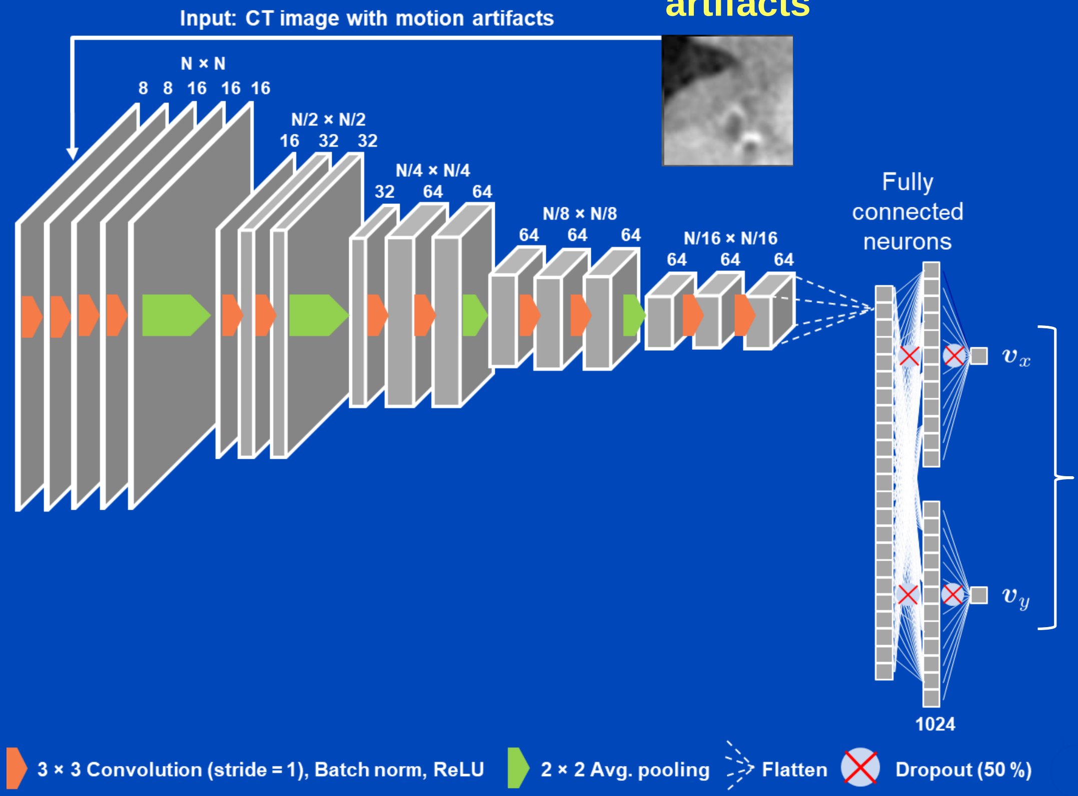


???

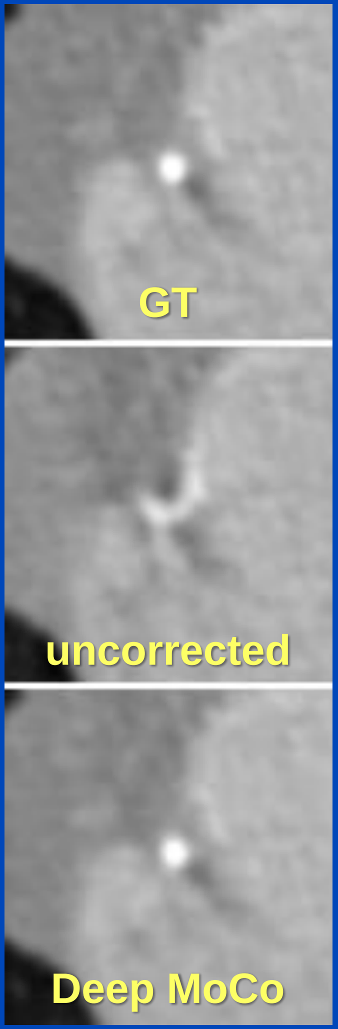


Motion Compensation for Cardiac CT

Input: CT image with motion artifacts



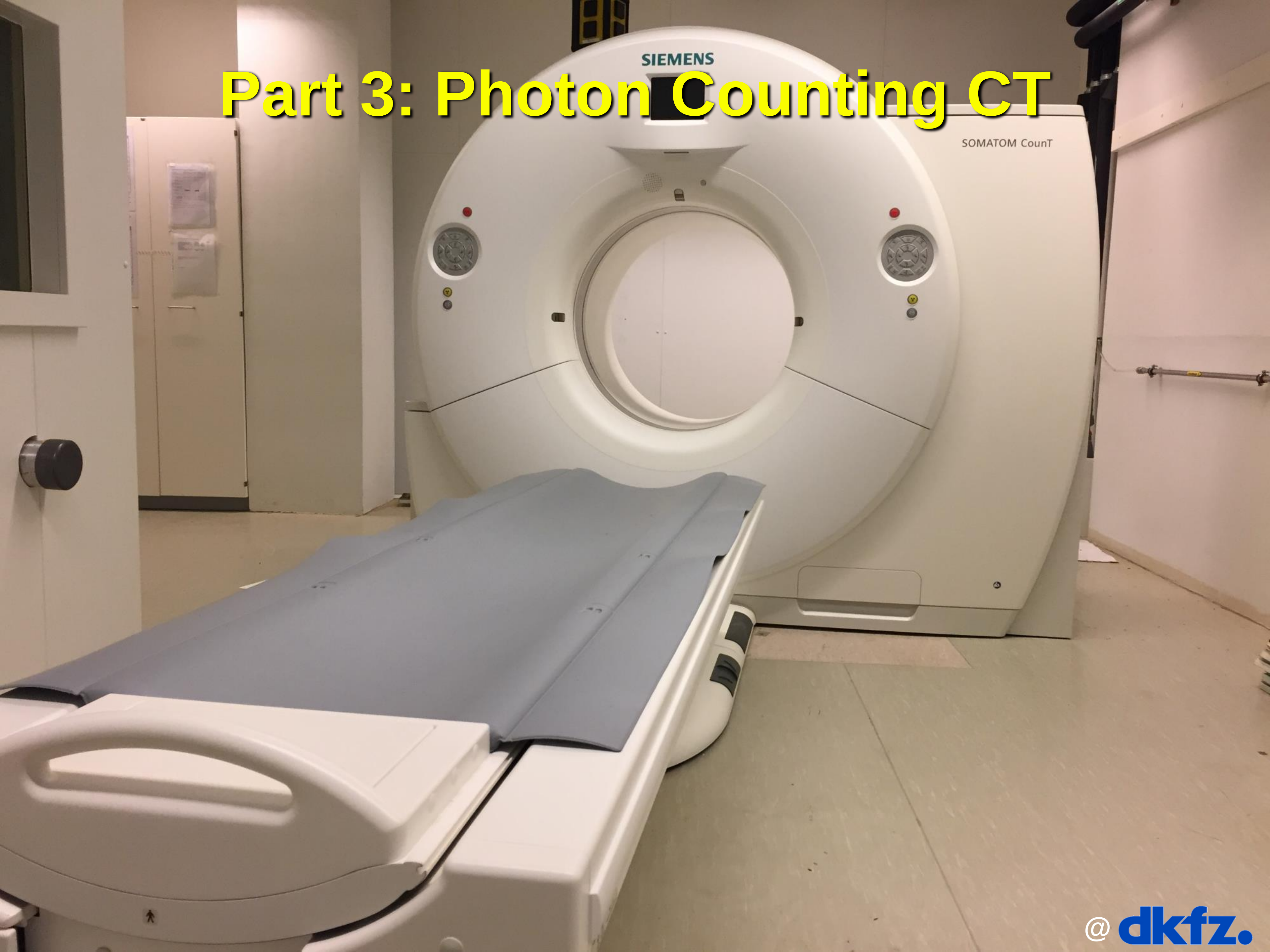
Output: motion direction (to be used by MoCo recon)



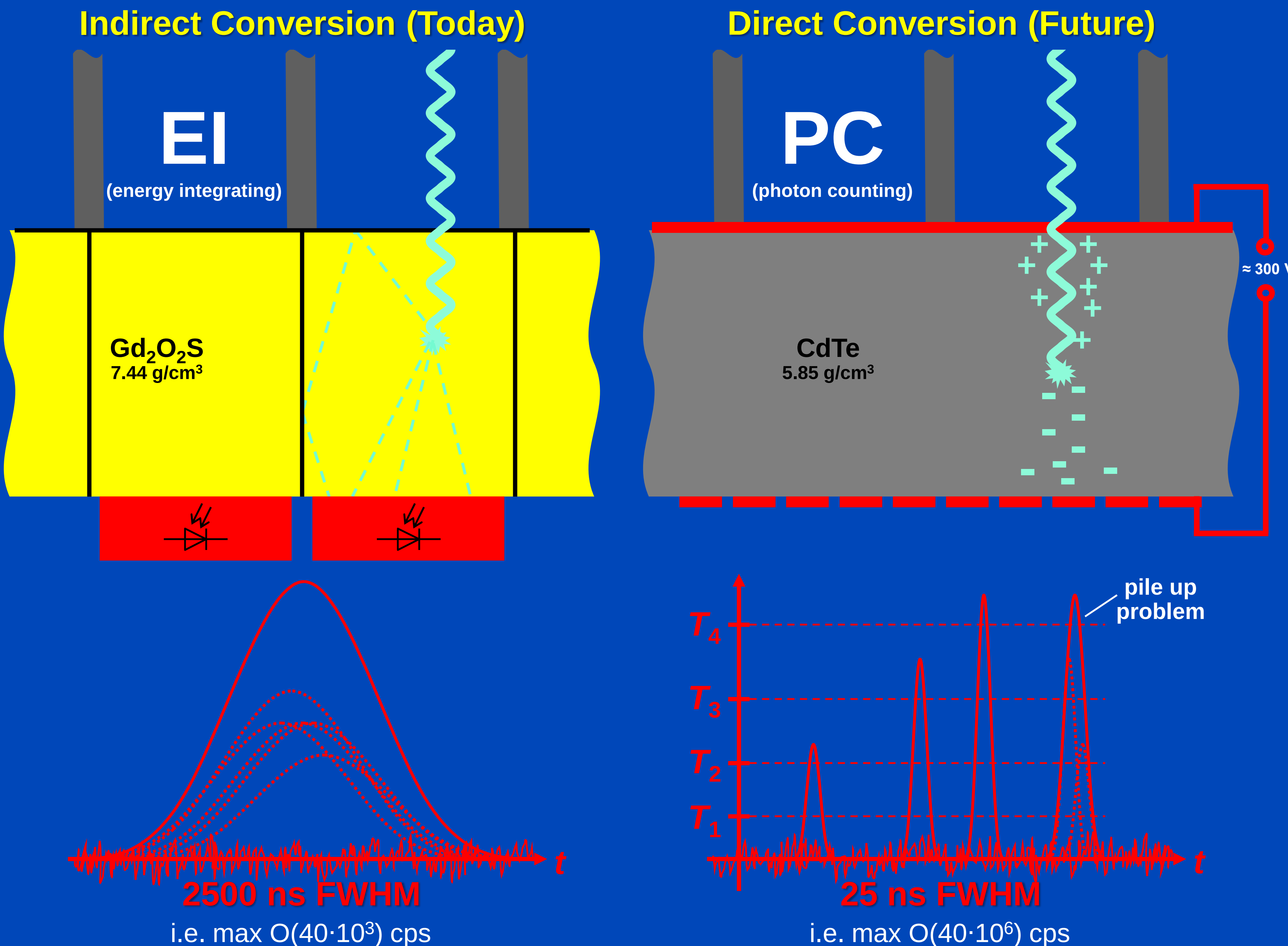
J. Maier, S. Lebedev, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, and M. Kachelrieß .Coronary artery motion compensation for short-scan cardiac CT using a spatial transformer network. Conference Program of the 6th International CT-Meeting, August 2020.

dkfz.

Part 3: Photon Counting CT



@ dkfz.



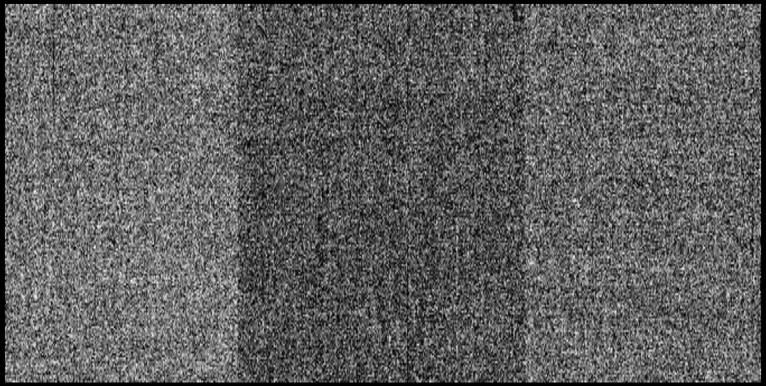
Requirements for CT: up to 10^9 x-ray photon counts per second per mm^2.
Hence, photon counting only achievable for direct converters.

Dark Image of Photon Counter Shows Background Radiation

18 frames, 5 min integration time per frame

Events per Frame

Energy Integrating (Dexela)



C/W = 0 a.u./70 a.u.

Photon Counting (Dectris Santis)

C/W = 1 cnts/2 cnts

Existing Systems 2020

	Setup	Detector	Pixel size (mm^2)	FOV	Thresholds	Acquisition rate info	Extra
Philips Healthcare (preclinical) [1, 2, 3]	Preclinical	CdZnTe	0.5 × 0.5	16.8 cm	5 (30-98 keV)	Frame rate: 2400 Hz	
MARS Bioimaging (preclinical) [4, 5]	Preclinical MARS orthopaedic imaging-cooming soon	2 mm CdZnTe; 5 medipix3RX chips in a row (70 mm × 14 mm)	0.11 × 0.11	10 cm	8 (10-120 keV)	Scan time: 8 minutes for a sample with 30 mm diameter and 15 mm length	Charge summing mode
Siemens Somaton CounT [6]	**Clinical, whole body**	Dual-source CT with one PC detector of 1.6 mm CdTe	0.225 × 0.225 or 0.45 × 0.45 or 0.9 × 0.9	**27.5 cm**	4 (20-90 keV)	4 kHz	
KTH Royal Institute of Technology, Stockholm [7]	Table-top Translating detector	30 mm Silicon strip	0.4 × 0.5	0.93 cm (need to translate the detector several times)	8	Count rate: 300 $Mcps/mm^2$	Edge-on design
Center for In Vivo Microscopy, Duke University, Durham (preclinical) [8, 9]	Preclinical Table-top	1 mm CdTe	0.15 × 0.15	~6.5 cm	4		
DKFZ	Preclinical	1 mm CdTe	0.15 × 0.15	~15 cm	4 (9-90 keV)	Frame rate 200 Hz Count rate 100 $Mcps/mm^2$	

Readout Modes of the Siemens CounT

Macro Mode
0.9 × 1.1 mm focus
2 readouts
16 mm z-coverage

12	12	12	12
12	12	12	12
12	12	12	12
12	12	12	12

Chess Mode
0.9 × 1.1 mm focus
4 readouts
16 mm z-coverage

12	34	12	34
34	12	34	12
12	34	12	34
34	12	34	12

Sharp Mode
0.9 × 1.1 mm focus
5 readouts
12 mm z-coverage

1	1	1	1
1	1	1	1
1	1	1	1
1	1	1	1

2	2	2	2
2	2	2	2
2	2	2	2
2	2	2	2

UHR Mode
0.7 × 0.7 mm focus
8 readouts
8 mm z-coverage

12	12	12	12
12	12	12	12
12	12	12	12
12	12	12	12

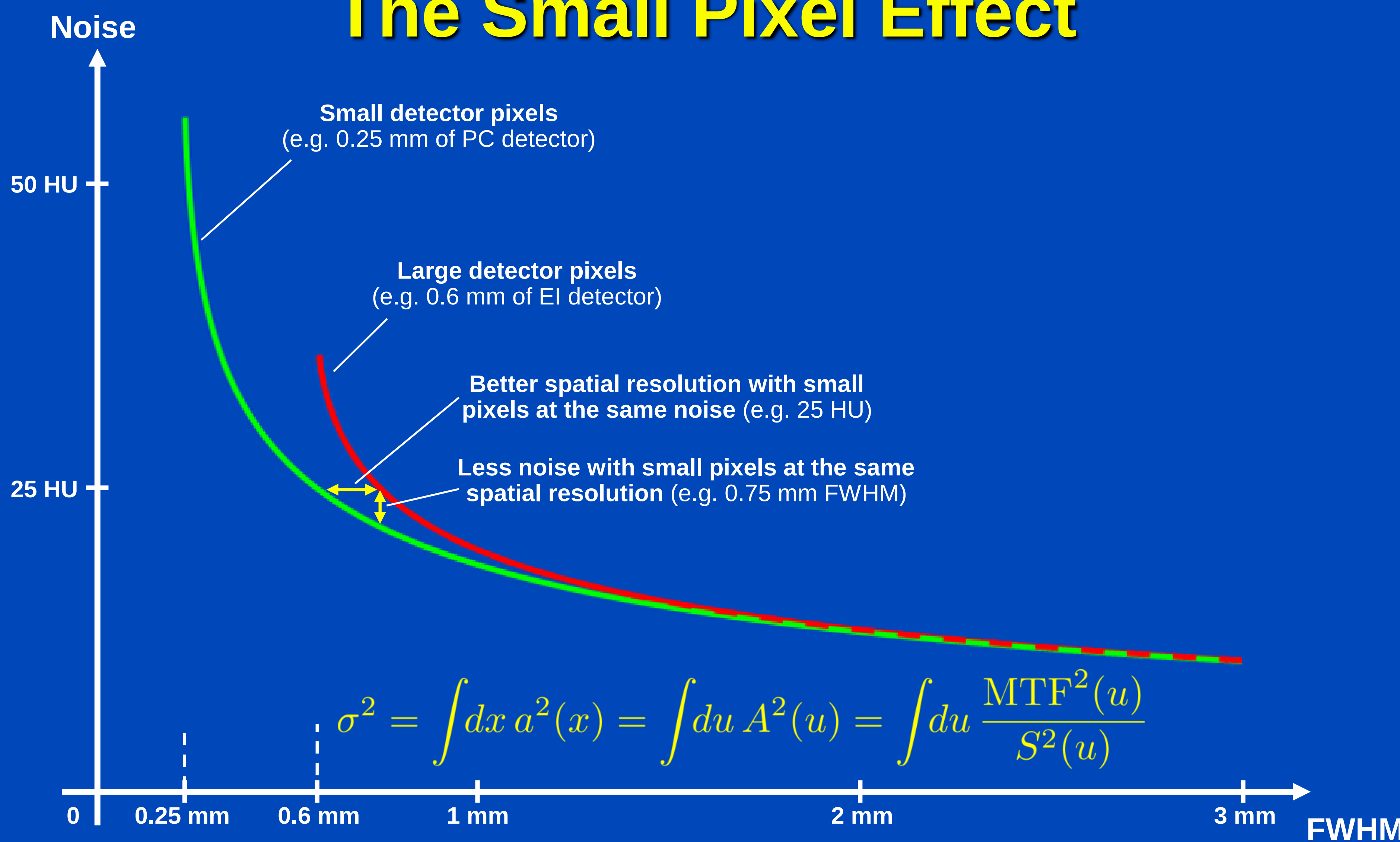
1.6 mm CdTe sensor. No FFS on detector B (photon counting detector). 4×4 subpixels of 225 µm size = 0.9 mm pixels (0.5 mm at isocenter). An additional 225 µm gap (e.g. for anti scatter grid) yields a pixel pitch of 1.125 mm.The whole detector consists of 128×1920 subpixels = 32×480 macro pixels.

This photon-counting whole-body CT prototype, installed at the Mayo Clinic, at the NIH and at the DKFZ is a DSCT system. However, it is restricted to run in single source mode. The second source is used for data completion and for comparisons with EI detectors.

Potential Advantages of Photon Counting CT

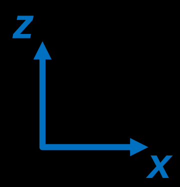
- No electronic noise
  - Less dose for infants
  - Less noise for obese patients
- Counting
  - Swank factor = 1 = maximal
  - Higher weights on low energies = good for iodine contrast
- Energy bin weighting
  - Lower dose/noise
  - Improved iodine CNR
- Smaller pixels (to avoid pileup)
  - Higher spatial resolution
  - Lower dose/noise at conventional resolution
- Spectral information on demand

The Small Pixel Effect

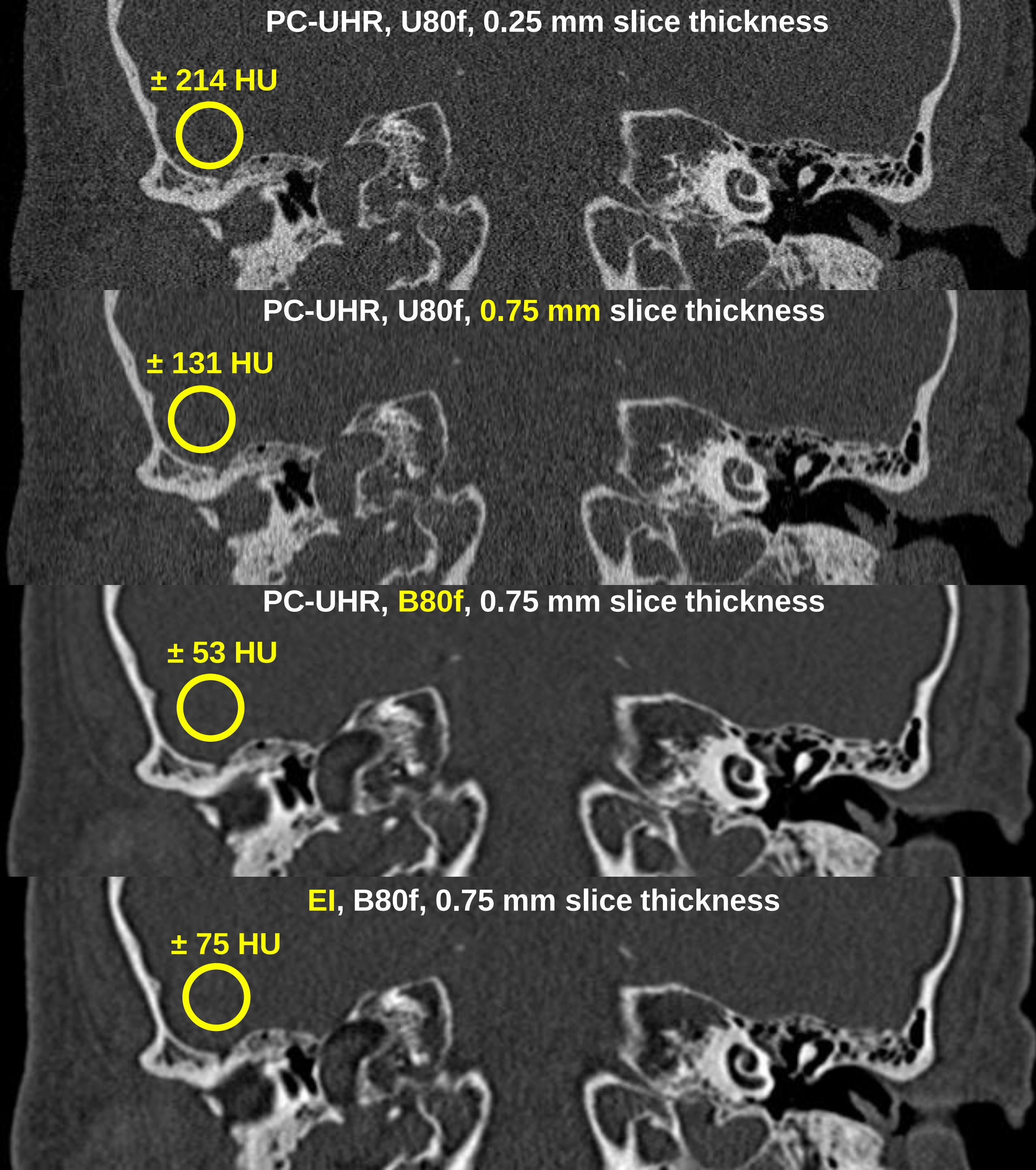


$$\sigma^2 = \int dx\, a^2(x) = \int du\, A^2(u) = \int du\, \frac{\mathrm{MTF}^2(u)}{S^2(u)}$$

All images reconstructed with 1024^2 matrix and 0.15 mm slice increment.
C = 1000 HU
W = 3500 HU



Data courtesy of the Institute of Forensic Medicine of the University of Heidelberg and of the Division of Radiology of the German Cancer Research Center (DKFZ)



10% MTF: 19.1 lp/cm
10% MTF:17.2 lp/cm
xy FWHM: 0.48 mm
z FWHM: 0.40 mm
$CTDI_{vol}$: 16.0 mGy

10% MTF: 19.1 lp/cm
10% MTF:17.2 lp/cm
xy FWHM: 0.48 mm
z FWHM: 0.67 mm
$CTDI_{vol}$: 16.0 mGy

10% MTF: 9.3 lp/cm
10% MTF:10.5 lp/cm
xy FWHM: 0.71 mm
z FWHM: 0.67 mm
$CTDI_{vol}$: 16.0 mGy

10% MTF: 9.3 lp/cm
10% MTF:10.5 lp/cm
xy FWHM: 0.71 mm
z FWHM: 0.67 mm
$CTDI_{vol}$: 16.0 mGy

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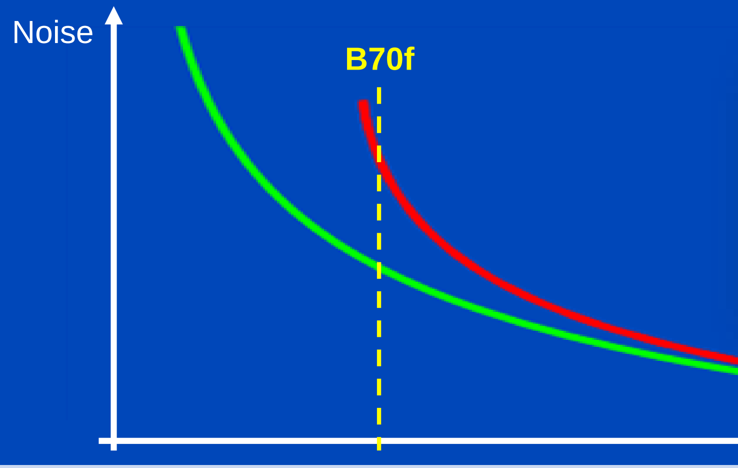
X-Ray Dose Reduction of B70f

PC vs. PC ("pixel effect only")

UHR vs. Macro	80 kV	100 kV	120 kV	140 kV
S	**23%** ± 12%	**34%** ± 10%	**35%** ± 11%	**25%** ± 10%
M	**32%** ± 10%	**32%** ± 8%	**35%** ± 8%	**34%** ± 9%
L	**35%** ± 10%	**29%** ± 15%	**27%** ± 9%	**31%** ± 11%

PC vs. EI ("pixel effect" and "iodine effect")

UHR vs. EI	80 kV	100 kV	120 kV	140 kV
S	**33%** ± 9%	**52%** ± 5%	**57%** ± 7%	**57%** ± 6%
M	**41%** ± 8%	**47%** ± 7%	**60%** ± 6%	**62%** ± 4%
L	**48%** ± 8%	**43%** ± 10%	**54%** ± 6%	**63%** ± 5%



Klein, Kachelrieß, Sawall et al. Invest. Radiol. 55(2), Feb 2020, in press

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Summary

- **CT dose efficiency and image quality will significantly improve**
  - Patient-specific prefilters
  - Deep learning-based image formation
  - Photon counting detectors
- **Less artifacts**
  - Iterative reconstruction
  - Deep learning-based image formation
- **Higher spatial resolution will become routinely available**
  - Conventional detectors with smaller pixels
  - Photon counting CT systems
- **Spectral information will be available on demand**
  - Photon counting detectors

Thank You!

This presentation is 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.