Options for Automatic Exposure Control

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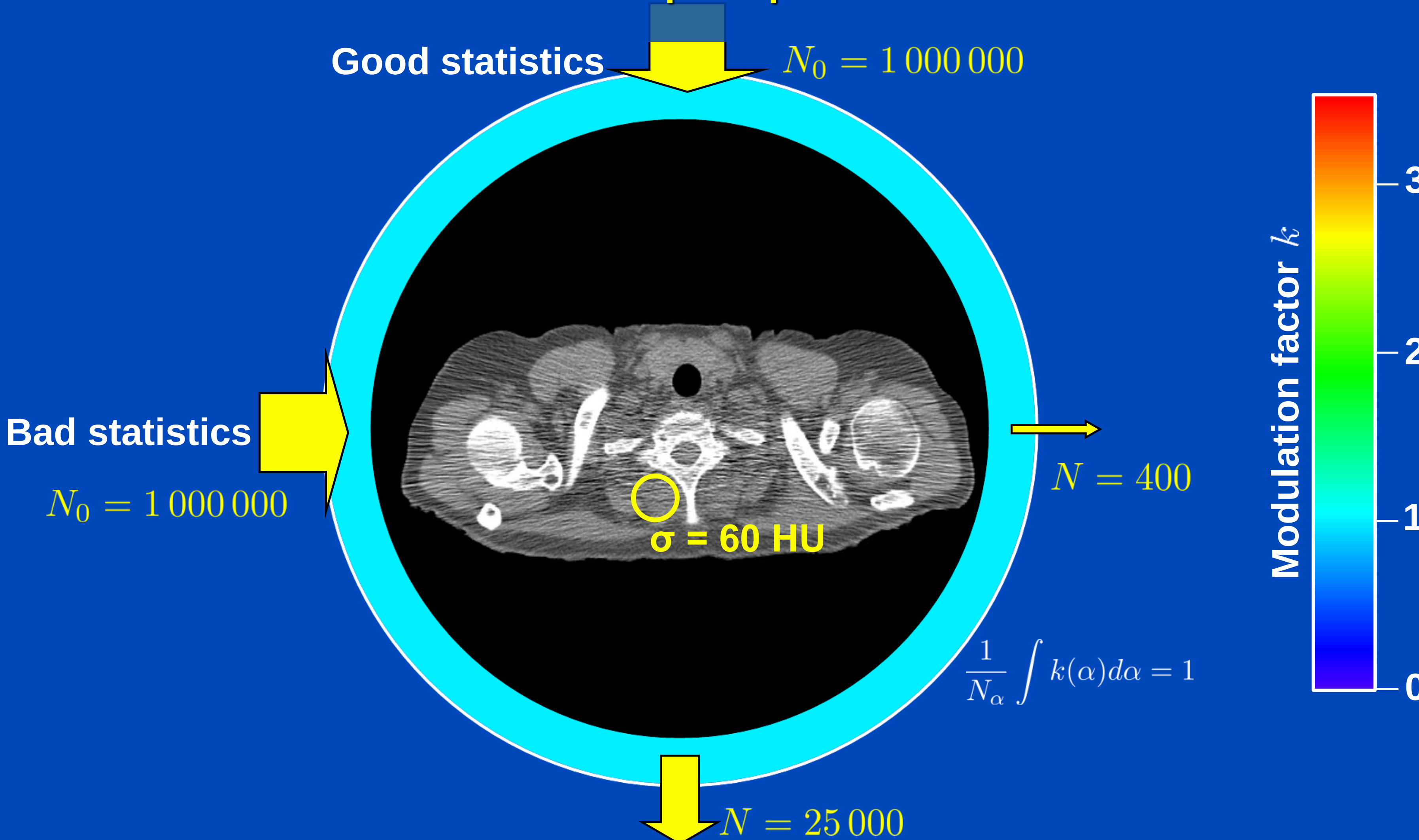
DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation & Outline

- Automatic exposure control (AEC) aims at setting the CT acquisition parameters automatically to reduce radiation dose while simplifying the workflow for radiologists.
- AEC covers:
  - Angular and longitudinal tube current modulation (TCM)
  - Automatic tube current selection
  - Automatic tube voltage selection
- Review of the basic principles of AEC and vendor specific implementations.
- Future applications: tube current modulation that minimizes the radiation risk, i.e. the effective dose.

Tube Current Modulation

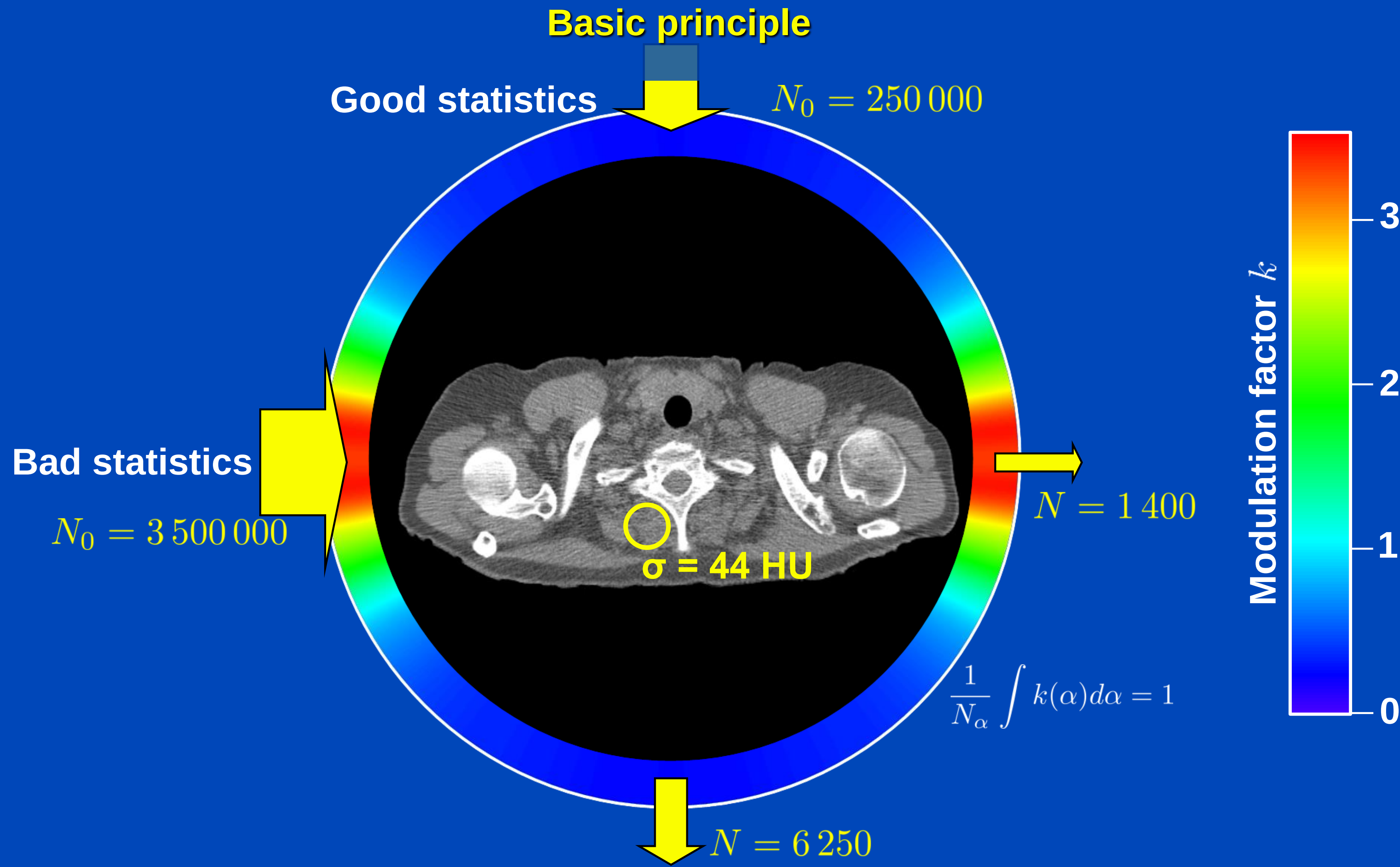
Basic principle



Constant tube current: High, inhomogeneous noise.

M. Gies, W. A. Kalender, H. Wolf, C. Suess, M. T. Madsen, "Dose reduction in CT by anatomically adapted tube current modulation. I. Simulation studies", Medical Physics 26 (11): 2235–2247 (1999).

Tube Current Modulation



Modulated tube current: Lower, more homogeneous noise.

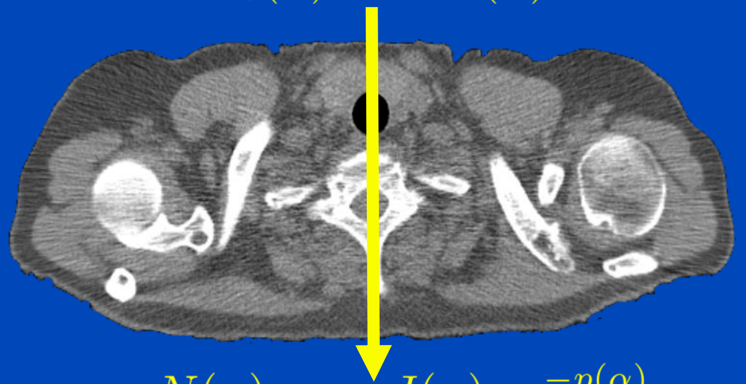
M. Gies, W. A. Kalender, H. Wolf, C. Suess, M. T. Madsen, "Dose reduction in CT by anatomically adapted tube current modulation. I. Simulation studies", Medical Physics 26 (11): 2235–2247 (1999).

Tube Current Modulation

From a mathematical perspective

- The tube current modulation curve $J(\alpha)$ is chosen such that the variance in the CT reconstruction is minimal

$$N_0(\alpha) = c \cdot J(\alpha)$$



$$N(\alpha) = c \cdot J(\alpha) \cdot e^{-p(\alpha)}$$

  – X-rays reaching the detector follow Poisson statistics: $\sigma^2_{N(\alpha)} = N(\alpha) = c \cdot J(\alpha) \cdot e^{-p(\alpha)}$

  – Variance propagation to projection domain yields: $\sigma^2_{p(\alpha)} = \dfrac{1}{c \cdot J(\alpha) \cdot e^{-p(\alpha)}}$

  – Variance propagation to image domain yields:

$$\sigma^2_f = \sum_\alpha \frac{1}{c \cdot J(\alpha) \cdot e^{-p(\alpha)}}$$

- Cost function:

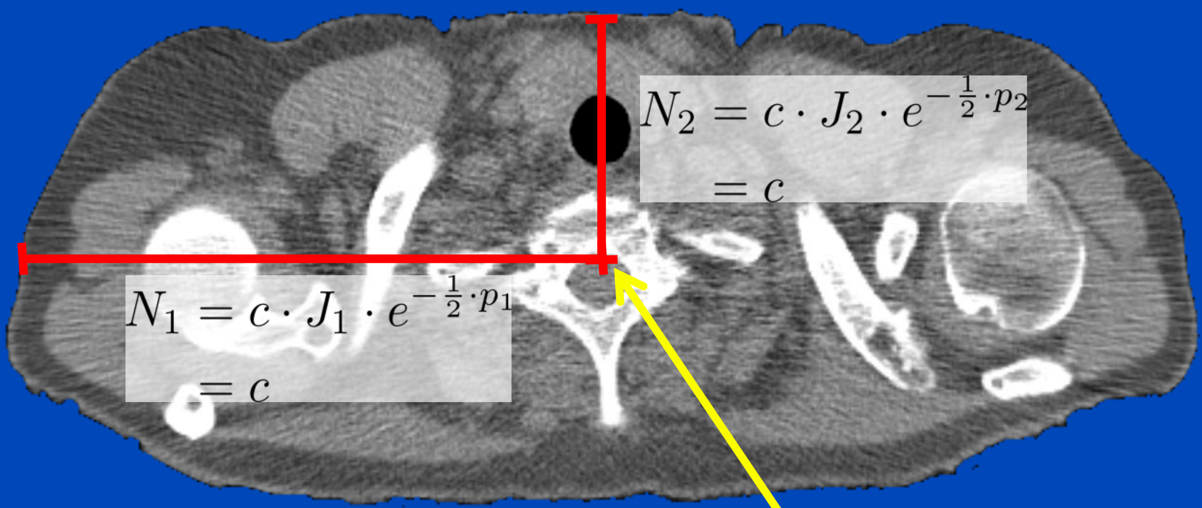
$$C = \sum_\alpha \frac{1}{c \cdot J(\alpha) \cdot e^{-p(\alpha)}} + \lambda \left(\sum_\alpha J(\alpha) - \text{const} \right)$$

- Minimization yields: $J(\alpha) \propto e^{\frac{1}{2} \cdot p(\alpha)}$

Tube Current Modulation

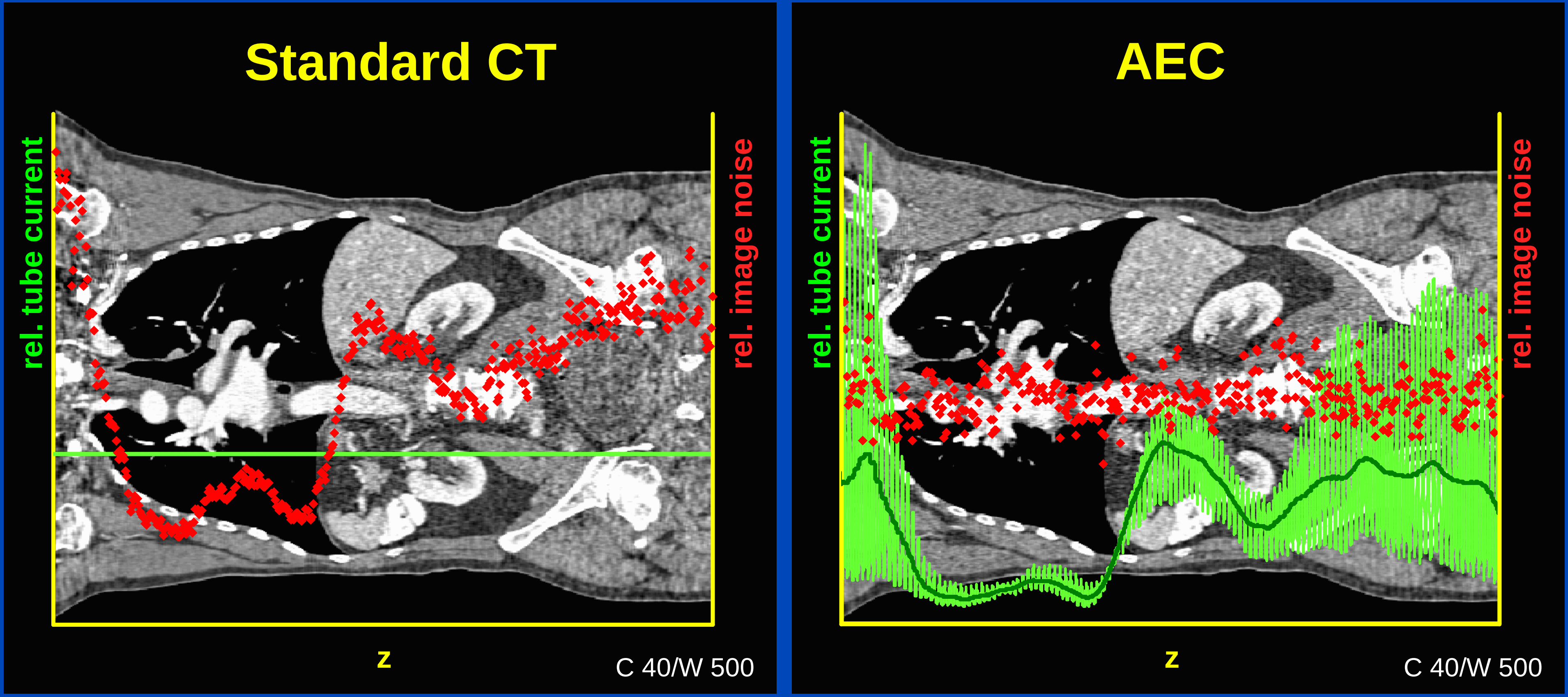
Interpretation

- **Tube current:** $J(\alpha) \propto e^{\frac{1}{2}\cdot p(\alpha)}$
- **Photon numbers:** $N(\alpha) = c \cdot J(\alpha) \cdot e^{-p(\alpha)}$



Rule of thumb:
The number of quanta reaching the center of the patient should be constant for all view angles.

Longitudinal and Angular Tube Current Modulation



34% mAs reduction with AEC at constant image quality for that specific case

Dose Reduction by Tube Current Modulation

Conventional scan: 327 mAs | **Online current modulation: 166 mAs**

Average dose reduction of 35% - 60 % has been reported[1]. 49% dose reduction in this case[2].

[1] M. Söderberg, M. Gunnarsson, Acta Radiologica 51 (6): 625–634 (2010).
[2] W. A. Kalender, H. Wolf, C. Suess, Med. Phys. 26 (11): 2248–2253 (1999).

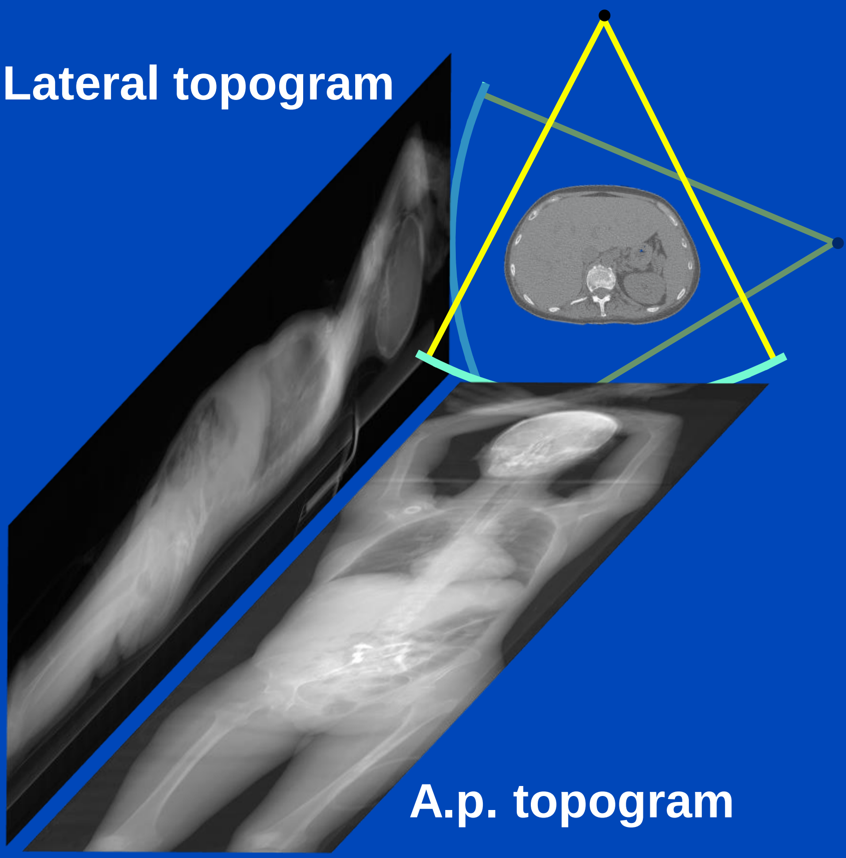
Features of AEC Systems

	Canon **SUREExposure 3D**	GE **AutomA 3D[1]**	Philips **DoseRight ACS**	Siemens **CARE Dose 4D**
mA adaptation for patient size	SUREExposure	AutomA	automatic current selection (ACS)	yes
mA adaption for z-dimension	SUREExposure	AutomA	Z-DOM, DOM	yes
mA adaption for α-angle	SUREExposure 3D	SmartmA	D-DOM	yes
Simultaneous application	xy-AEC can be chosen separately	AutomA + SmartmA = AutomA 3D	ACS+Z-DOM or ACS+D-DOM, but not ACS+Z-DOM+D-DOM	always on
Method to determine the exposure level	standard deviation	noise index	reference image	reference mAs
Basis for AEC for z-position / α-angle	a.p. and lateral topogram / sinusoidal modulation	single topogram / sinusoidal modulation	a.p. and lateral topogram / previously acquired 180° data	a.p. and lateral topogram / previously acquired 180° data

DOM = dose modulation = TCM = tube current modulation
[1]Feature is disabled when in fast tube voltage switching DECT mode

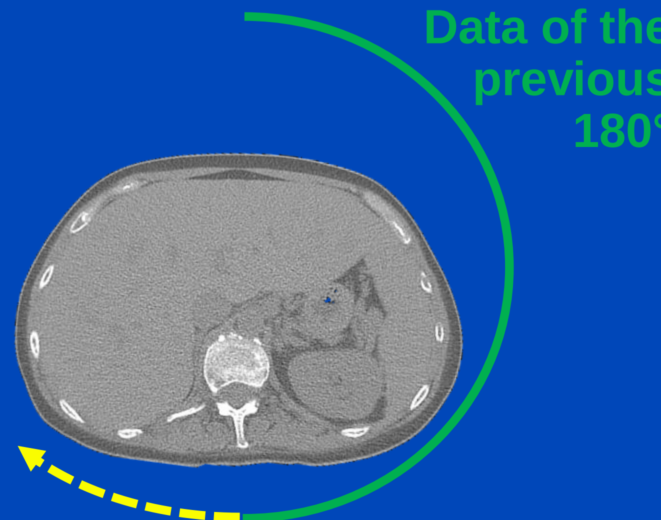
Determination of the Patient Attenuation

From topogram / scout scan



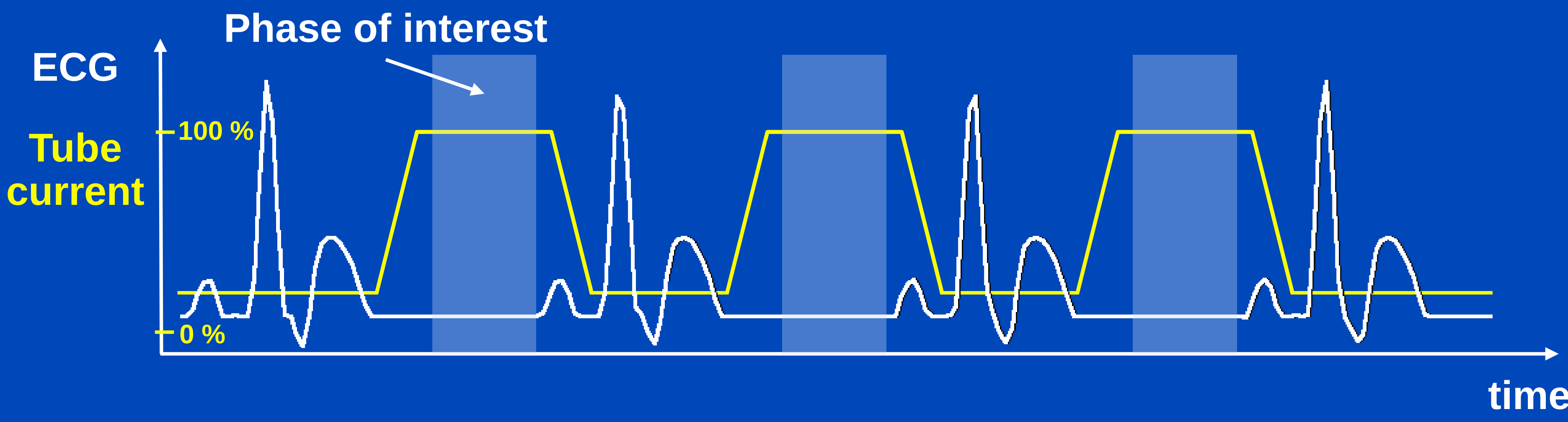
→ Predictive calculations or sinusoidal interpolation between a.p. and lateral views

From previously acquired data



→ Online feedback loop that makes use of the previously acquired 180° data

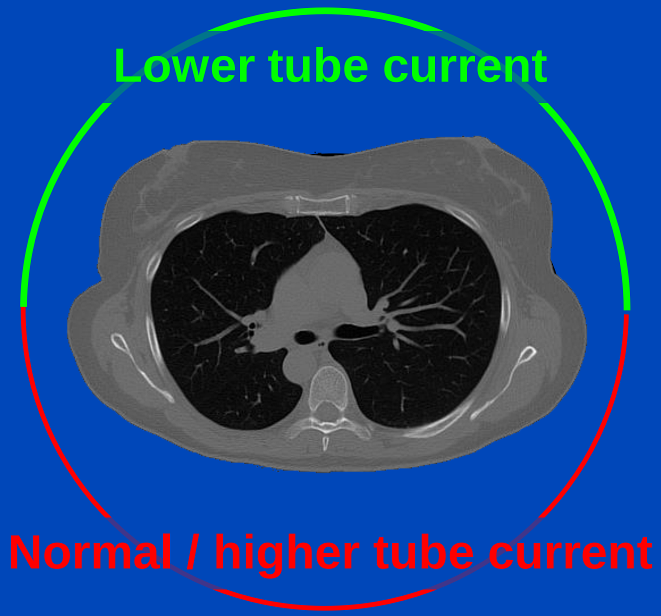
ECG-Based Tube Current Modulation



	Canon $^{\text{SURE}}$Exposure 3D	GE AutomA 3D	Philips DoseRight ACS	Siemens CARE Dose 4D
Modulation for cardiac CT - retrospective	"ECG Modulation"	"ECG Modulated mA"	DoseRight Cardiac "Step and Shoot"	"Adaptive ECG-Pulsing"
Modulation for cardiac CT - prospective	"$^{\text{SURE}}$Cardio Prospective"	"Prospective Gating"	DoseRight Cardiac ECG triggered dose modulation	Prospective sequence scan = "Adaptive Cardio" + "Pulsing", prospective spiral scan = "Flash mode"

Organ-Specific Tube Current Modulation

- **Limit the radiation exposure of sensitive organs at the anterior body surface (breast, thyroid glands, eyes).**
- **Tube current is lowered in a 120° to 180° interval in front of the organ.**
- **Tube current may be increased for posterior-anterior views to maintain image quality.**



	Canon SURE**Exposure 3D**	GE **AutomA 3D**	Philips **DoseRight ACS**	Siemens **CARE Dose 4D**
Organ-Specific AEC/TCM	OEM, Decrease anterior tube current	ODM, Decrease anterior tube current	Liver DRI, Different image quality setting for the liver	X Care, Decrease anterior tube current, increase posterior tube current

Automatic Tube Voltage Selection

80 kV	100 kV	120 kV

All CT images are simulated with the same dose

C = 100 HU,
W = 600 HU

Iodine CNR: 19.1	Iodine CNR: 16.7	Iodine CNR: 14.7
Soft tissue CNR: 3.1	Soft tissue CNR: 3.2	Soft tissue CNR: 3.3

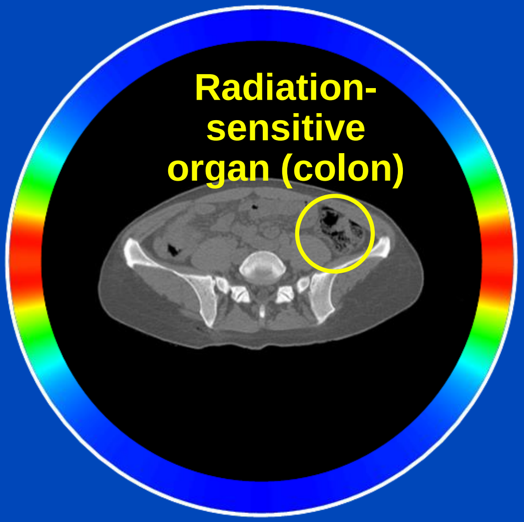
	Canon **SUREExposure 3D**	GE **AutomA 3D**	Philips **DoseRight ACS**	Siemens **CARE Dose 4D**
Automatic tube voltage selection	Sure kV	kV Assist	-	CARE kV

Can we get any better?

TCM Minimizing the Radiation Risk

Motivation

- Conventional tube current modulation approaches can only account for a few organs.
- Conventional tube current modulation approaches do not have access to the actual dose distribution, but are based on minimizing the mAs product.



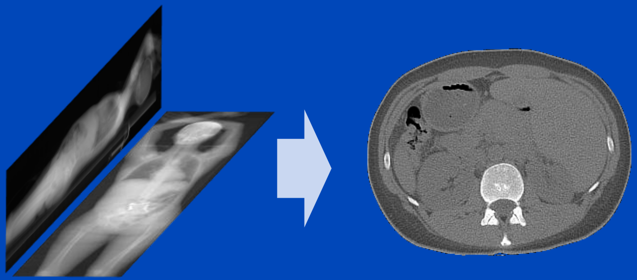
➡ Additional prior knowledge may enable more sophisticated approaches.

- Here: Use deep learning-based prior knowledge to perform a tube current modulation that minimizes the radiation risk, i.e. the effective dose.

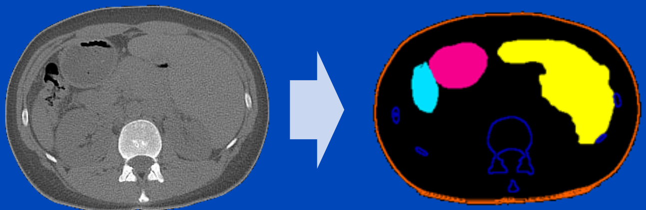
TCM Minimizing the Radiation Risk

Basic workflow

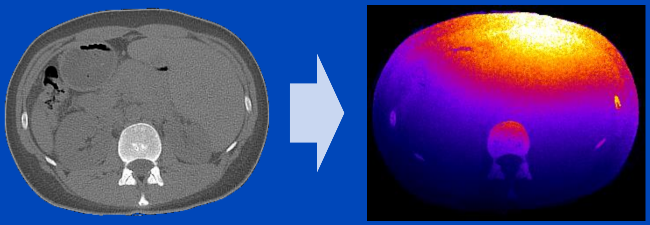
1. Coarse reconstruction from two scout views



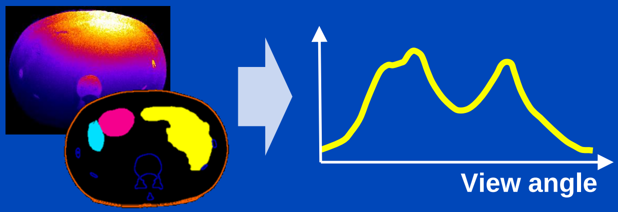
2. Segmentation of radiation-sensitive organs



3. Calculation of the effective dose per view using the deep dose estimation (DDE)



4. Determination of the tube current modulation curve that minimizes the radiation risk

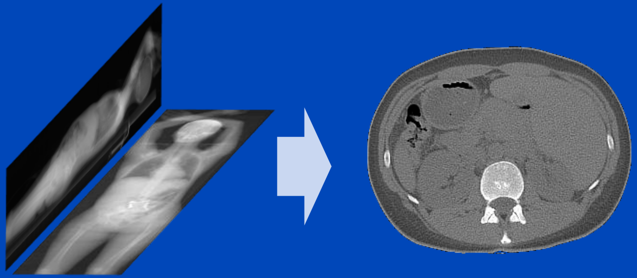


TCM Minimizing the Radiation Risk

Basic workflow

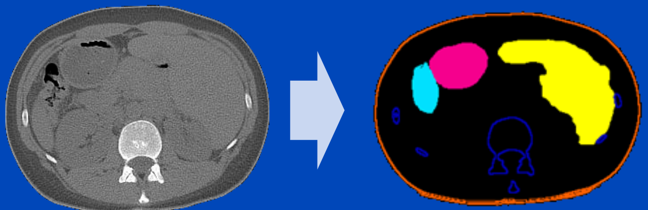
1. **Coarse reconstruction from two scout views**

   X. Ying, et al., "X2CT-GAN: Reconstructing CT From Biplanar X-Rays With Generative Adversarial Networks," *CVPR 2019*

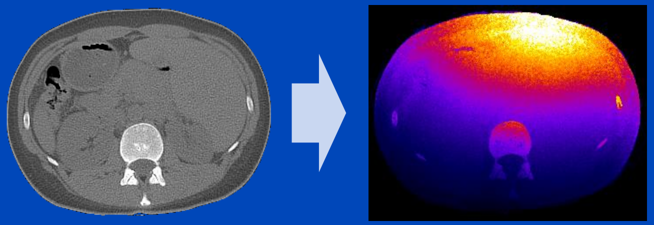


2. **Segmentation of radiation-sensitive organs**

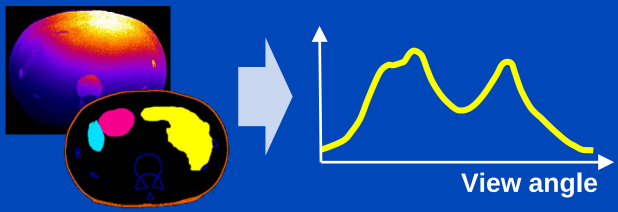
   S. Chen, M. Kachelrieß et al., "Automatic multi-organ segmentation in dual-energy CT (DECT) with dedicated 3D fully convolutional DECT networks." Med. Phys. 2019



3. **Calculation of the effective dose per view using the deep dose estimation (DDE)**



4. **Determination of the tube current modulation curve that minimizes the radiation risk**

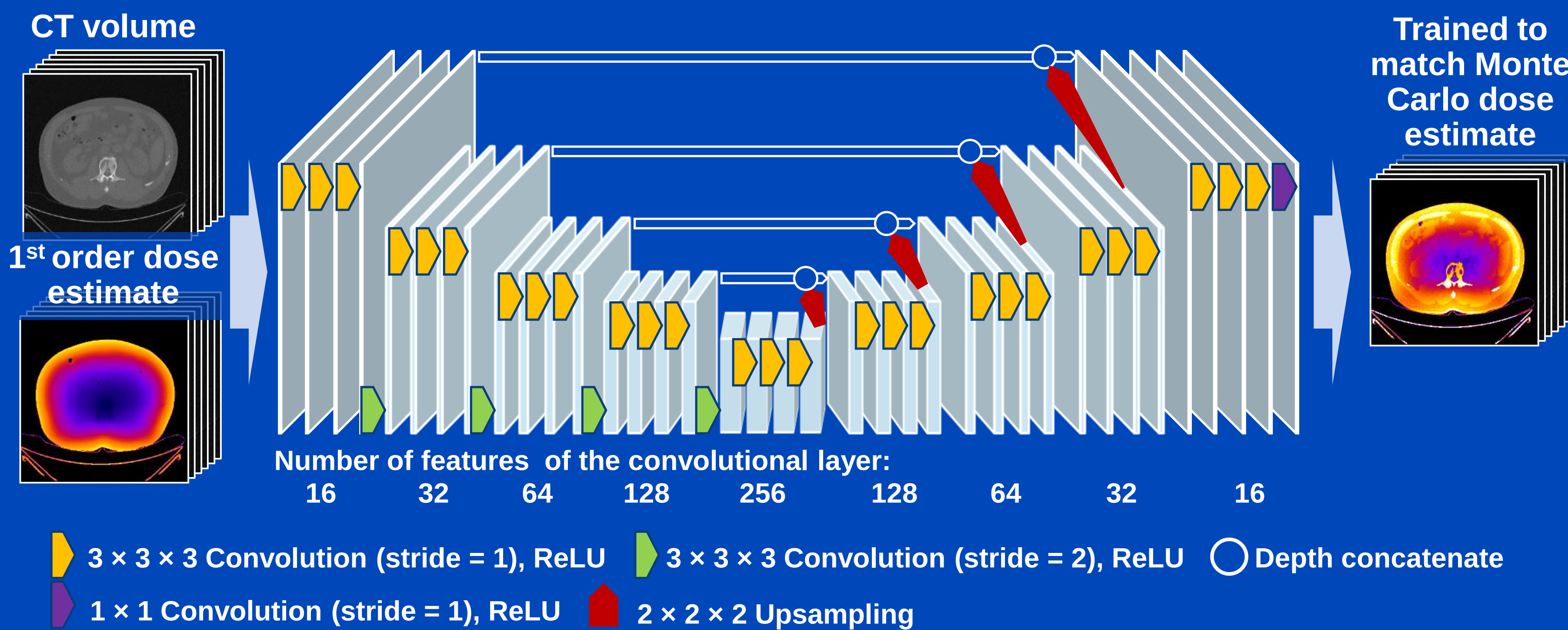


Deep Dose Estimation (DDE)

Basic principle

- Monte Carlo (MC) simulation is the gold standard for patient-specific dose estimation, but too slow to be applied routinely.

⇨ Training of a deep convolution to reproduce MC simulations given only the CT image and a 1st order dose estimate as input.



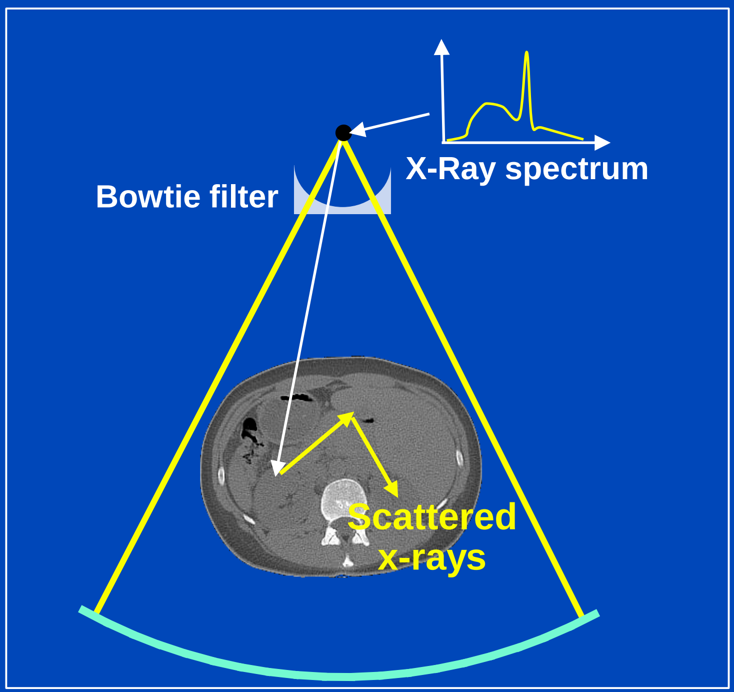
J. Maier, E. Eulig, S. Dorn, S. Sawall, M. Kachelrieß, in *Proceedings of the IEEE Nuclear Science Symposium and Medical Imaging Conference* (2018).

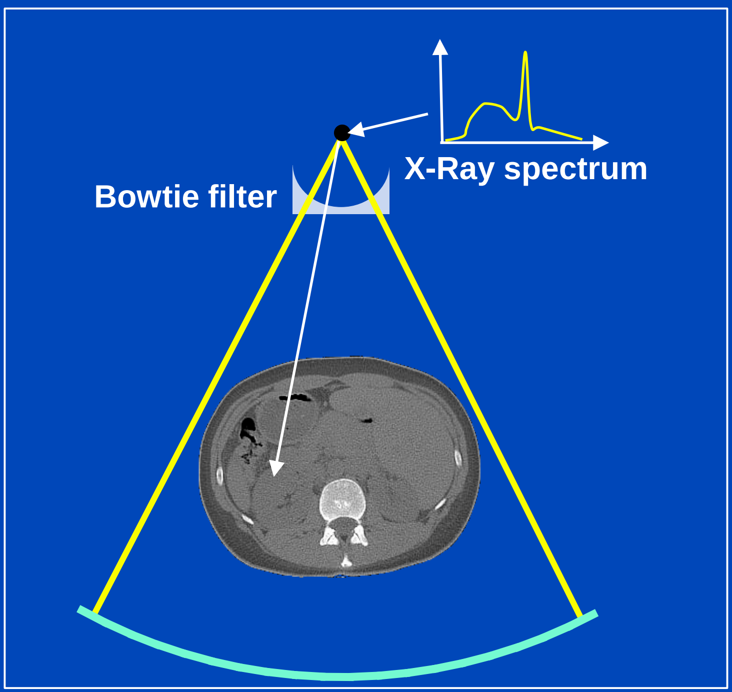
Deep Dose Estimation (DDE)

First order dose estimate

Monte Carlo:
Calculation of the complete photon trajectory through different tissues including scatter interactions.
→ Slow

First order dose:
Only direct rays are considered. Only a single material (water with the patient's density distribution) is considered.
→ Fast





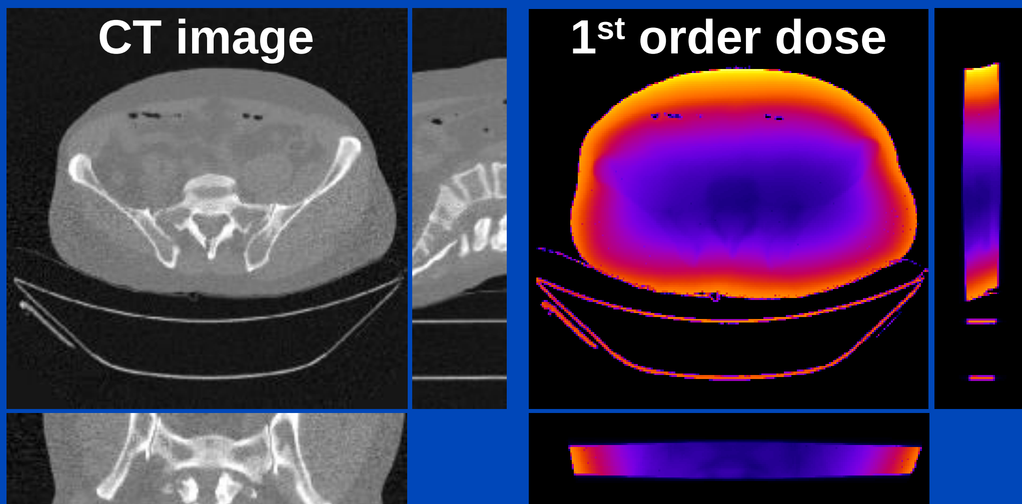
Deep Dose Estimation (DDE)

Training data

- 35 full body scans were used to generate training data for the deep dose estimation.
- Different patients were used for training and testing.
- CT scans were simulated using the following parameters:
  - Anatomies: Head, thorax, abdomen, pelvis
  - Tube voltages: 70 kV – 150 kV,
  - Scan trajectories: circular, spiral
  - Shaped filters: with and without bowtie
  - Angular coverage: 10°, 360°
- The DDE network was trained for 100 epochs on an Nvidia Quadro P6000 GPU using the mean absolute percentage error as loss function.

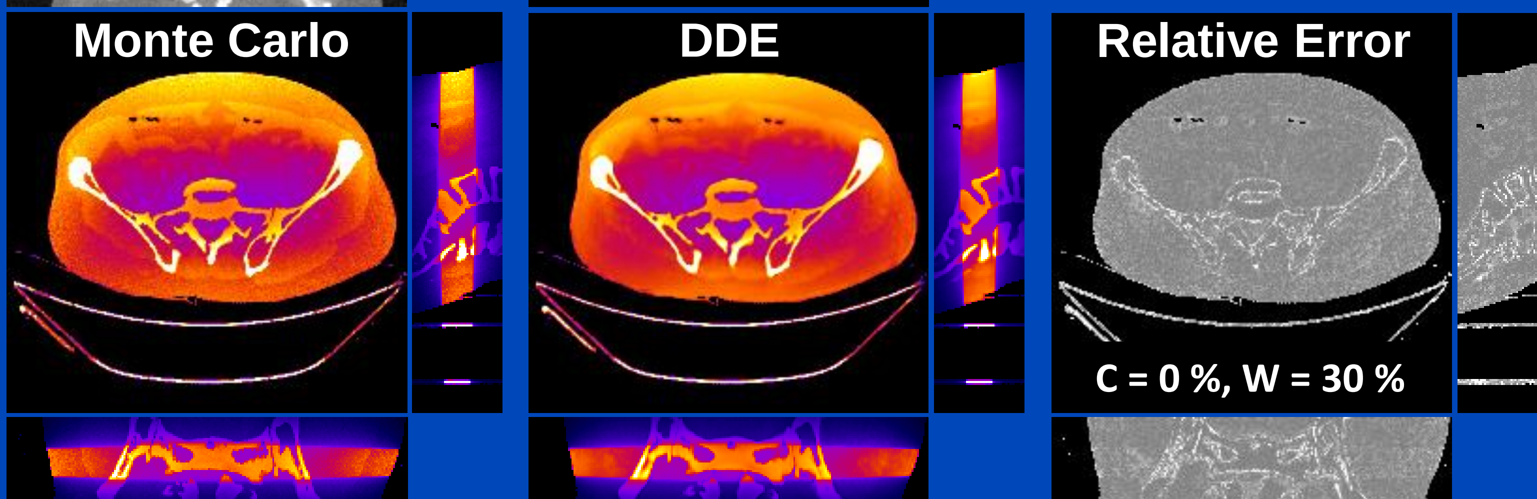
Deep Dose Estimation (DDE)

Dose predictions, 360° scans



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

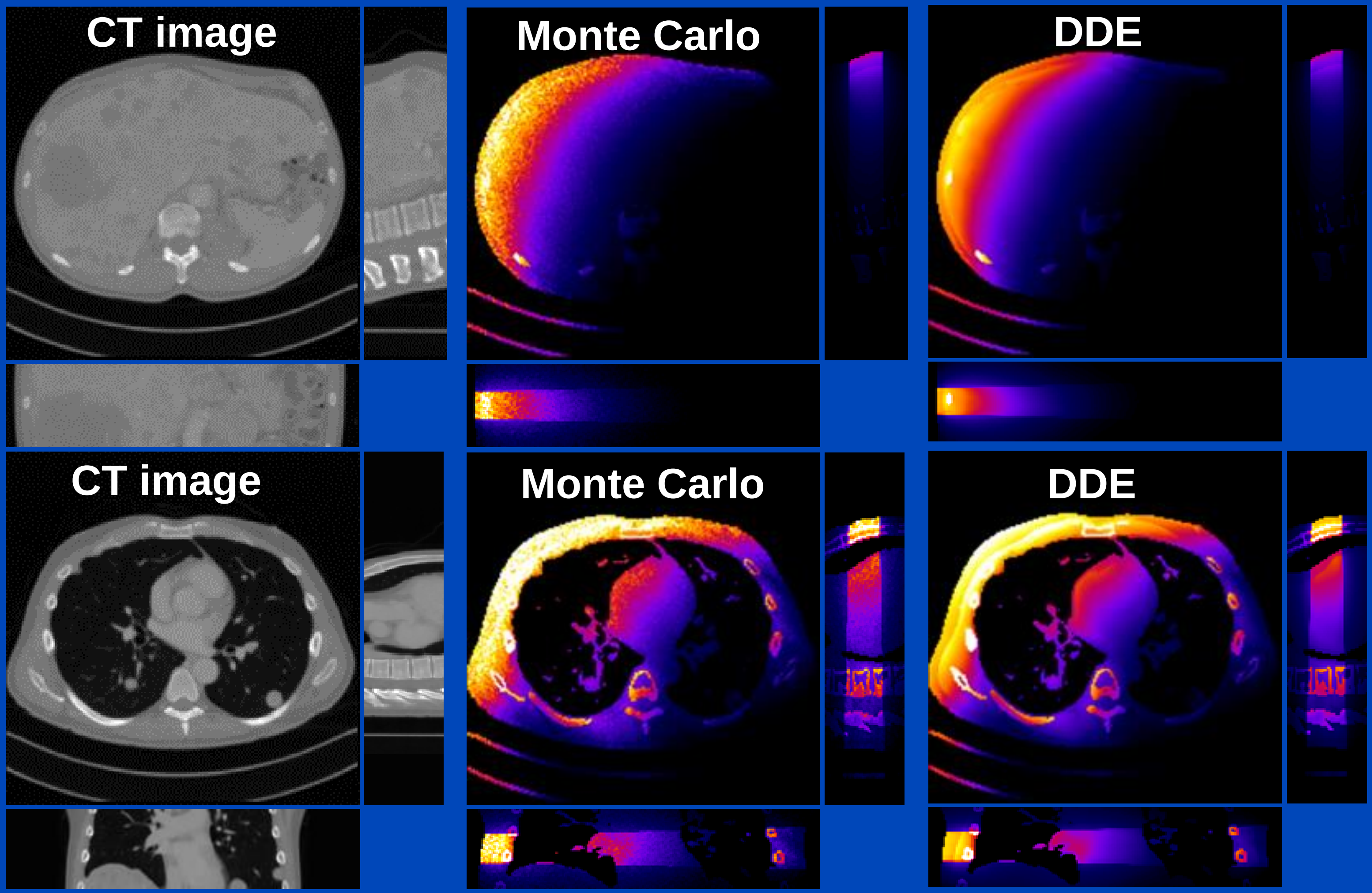
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P6000 GPU



Mean relative error on the testing data set: 5 %

Deep Dose Estimation (DDE)

Dose predictions, 10° scans



Mean relative error on the testing data set: 5 %

TCM Minimizing the Radiation Risk

Determination of the modulation curve

- Calculation of dose estimates for 10° segments using the deep dose estimation
- Calculation of the effective dose according to the ICRP weighting factors for every 10° segment:

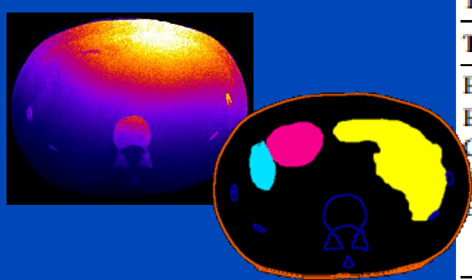


Table 3. Recommended tissue weighting factors.

Tissue	w_T	$\sum w_T$
Bone-marrow (red), Colon, Lung, Stomach, Breast, Remainder tissues*	0.12	0.72
Gonads	0.08	0.08
Bladder, Oesophagus, Liver, Thyroid	0.04	0.16
Bone surface, Brain, Salivary glands, Skin	0.01	0.04
	Total	1.00

$$D_{\mathrm{eff}}(\alpha) = \sum_T w_T \cdot D_T(\alpha)$$

- New cost function:

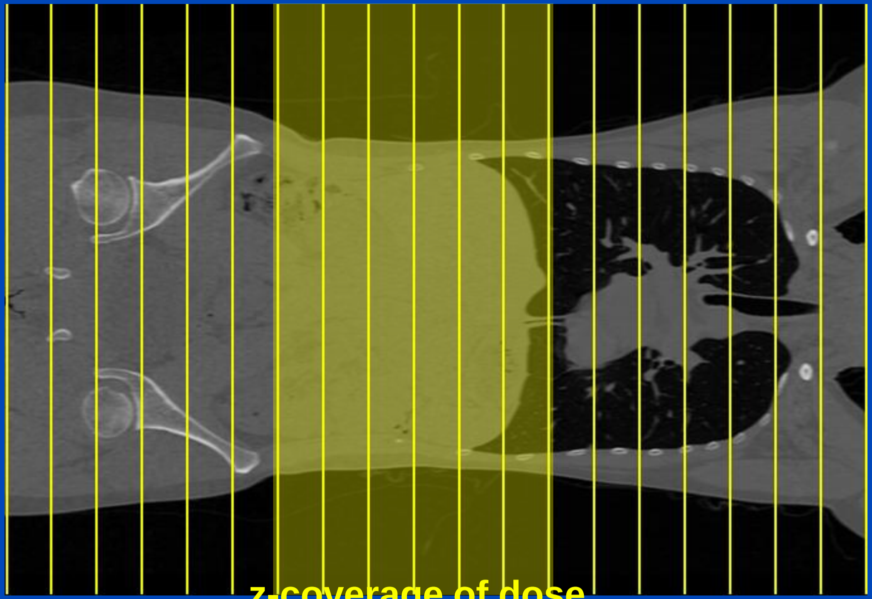
$$C = \underbrace{\sum_\alpha \frac{1}{c \cdot J(\alpha) \cdot e^{-p(\alpha)}}}_{\text{Image variance}} + \lambda \underbrace{\left(\sum_\alpha J(\alpha) \cdot D_{\mathrm{eff}}(\alpha) \right)}_{\text{Effective dose}} \xrightarrow{\text{Minimization}} J(\alpha) \propto \frac{e^{\frac{1}{2} \cdot p(\alpha)}}{\sqrt{D_{\mathrm{eff}}(\alpha)}}$$

Simulation Study

- Simulation of CT scans covering different anatomies at 70 kV, 120 kV, and 150 kV (6 mm Al prefiltration).
- Simulation of consecutive circle scans (38.4 mm apart), each with a z-collimation of 38.4 mm.

Axial view

Coronal view



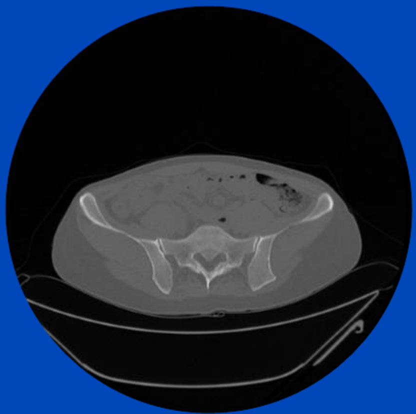
Modulation Curves 70 kV

Angular modulation, nz = 6

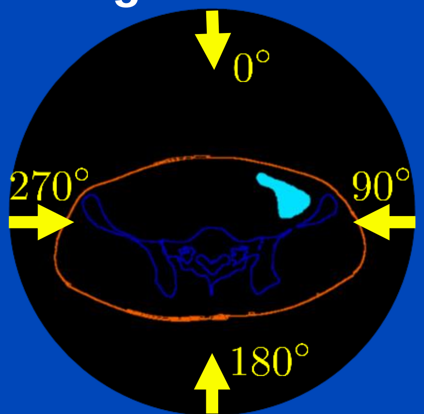
Organ / weight

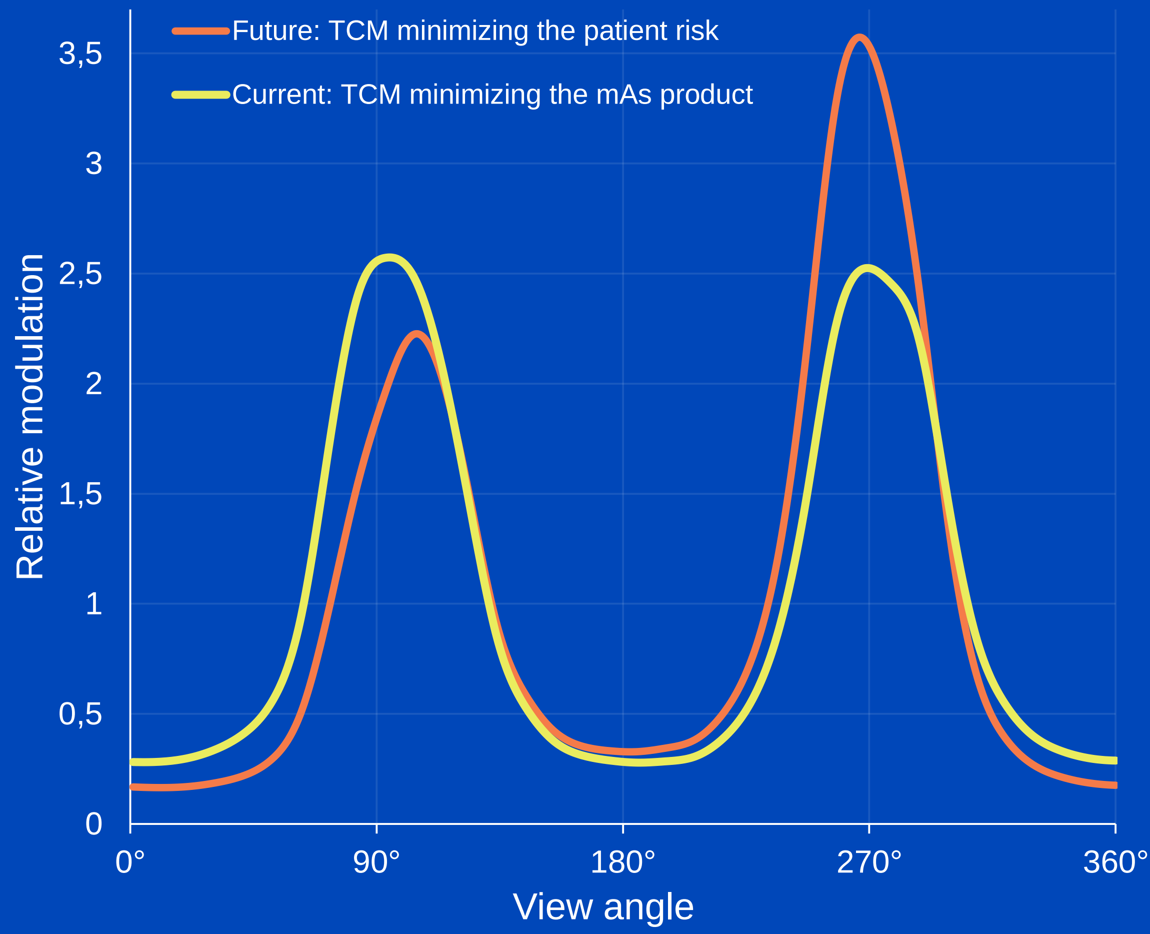
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



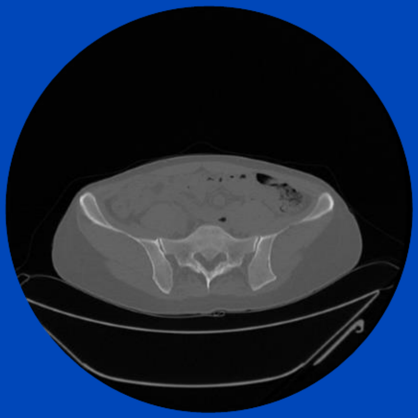


Modulation Curves 120 kV

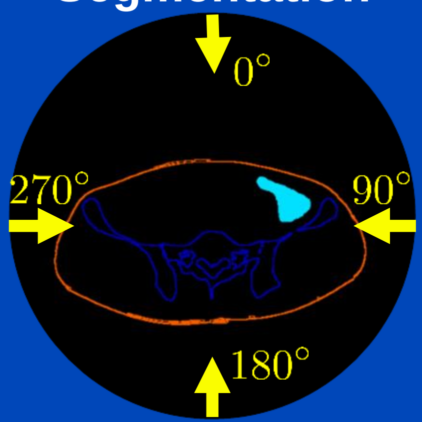
Angular modulation, nz = 6

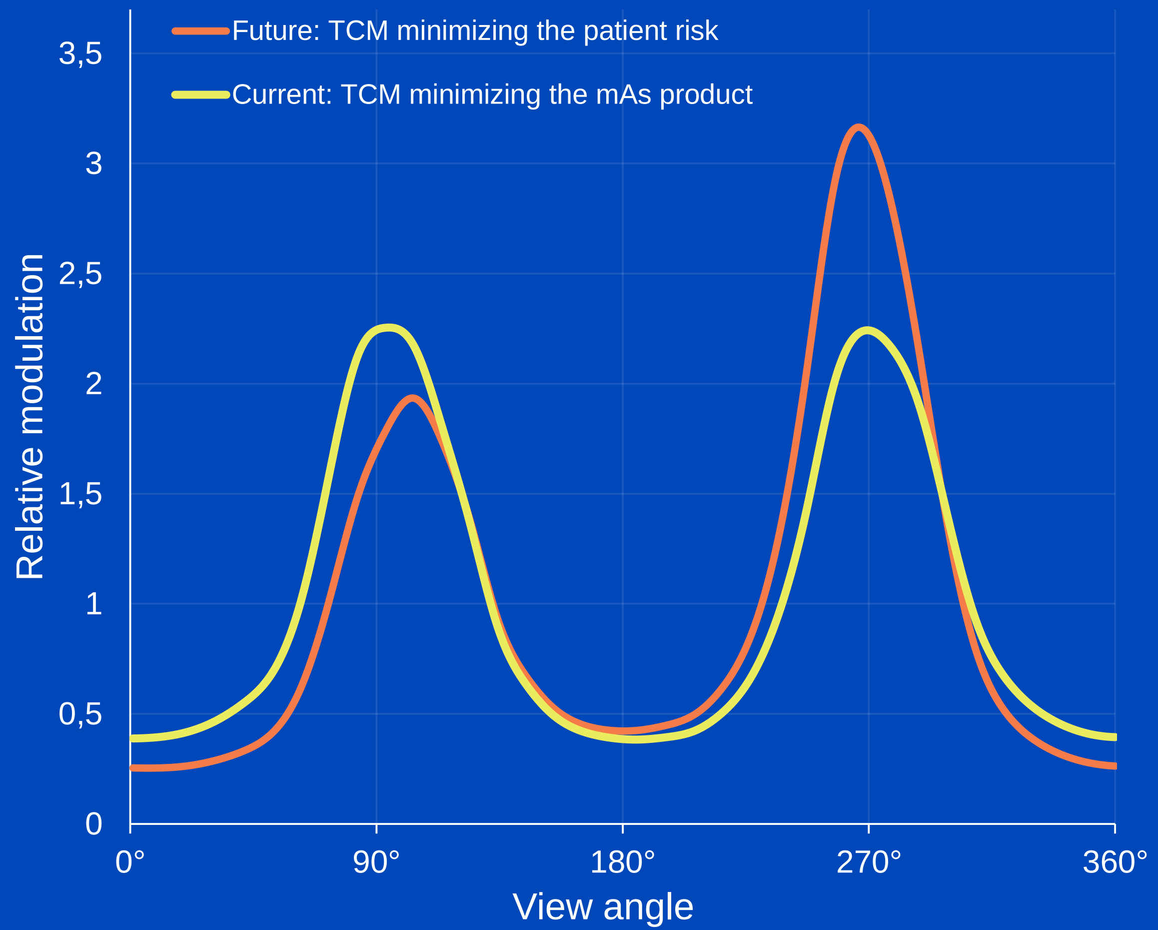
Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



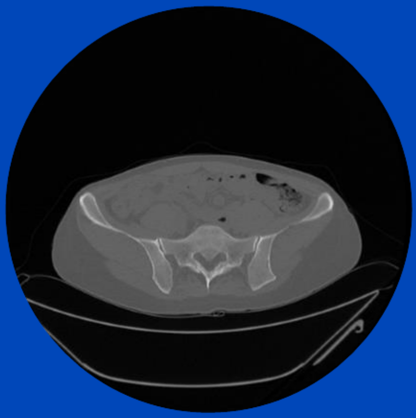


Modulation Curves 150 kV

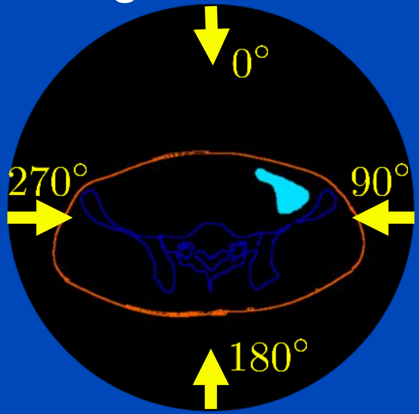
Angular modulation, nz = 6

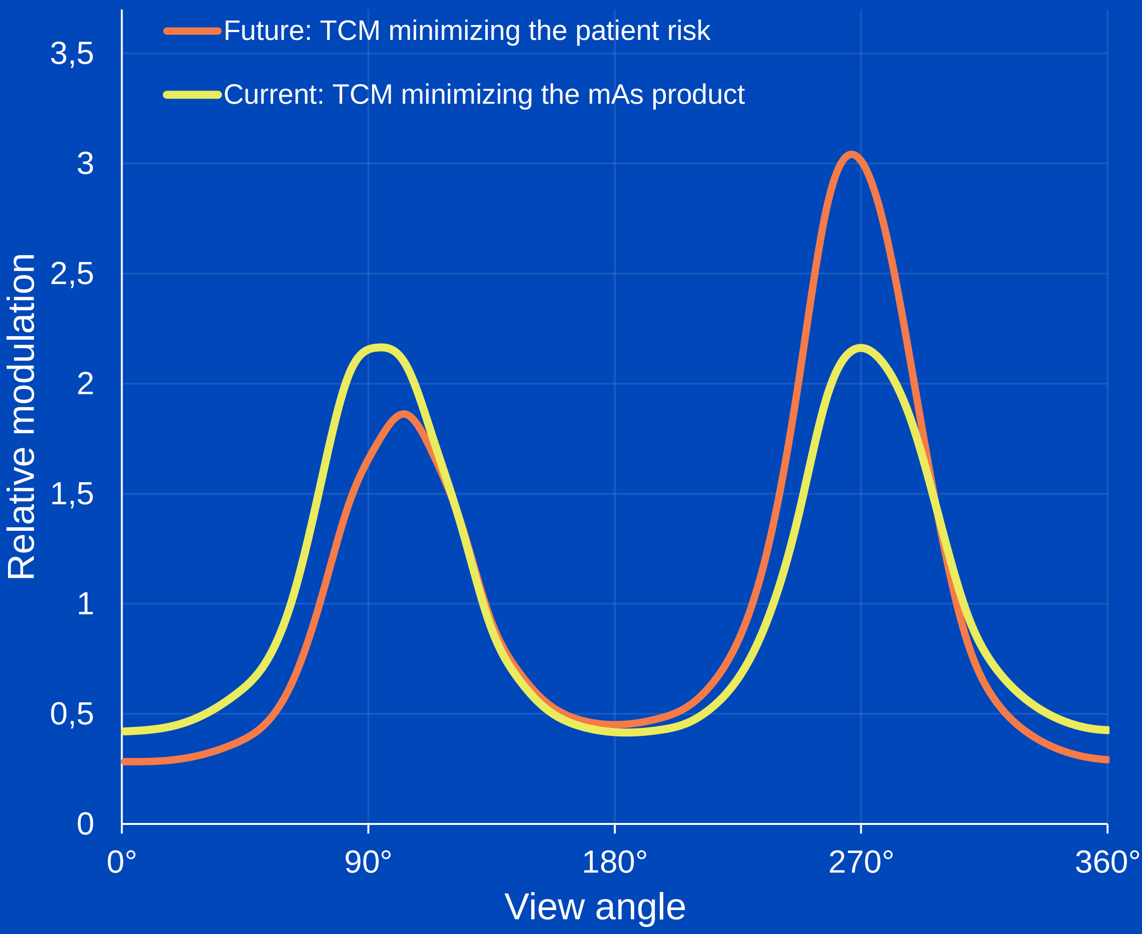
Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



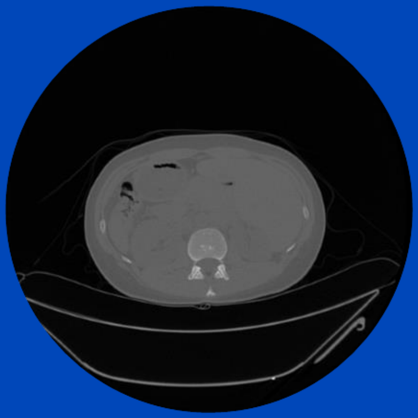


Modulation Curves 70 kV

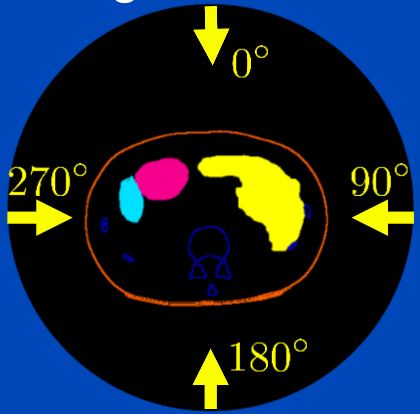
Angular modulation, nz = 10

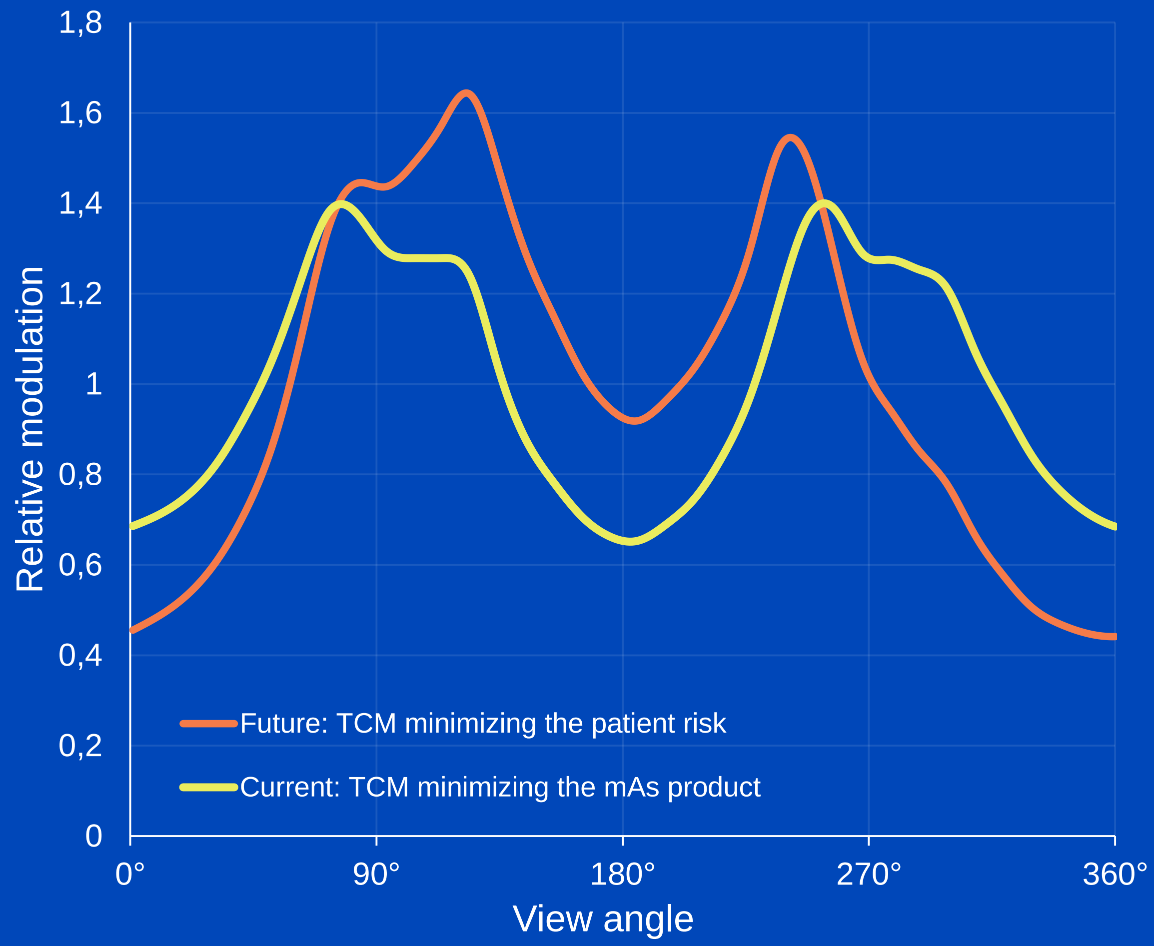
Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



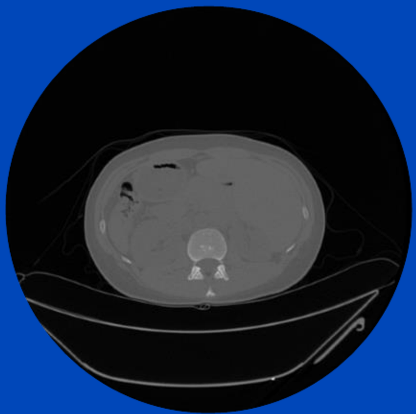


Modulation Curves 120 kV

Angular modulation, nz = 10

Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



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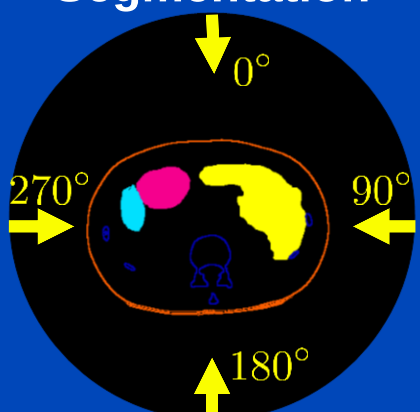
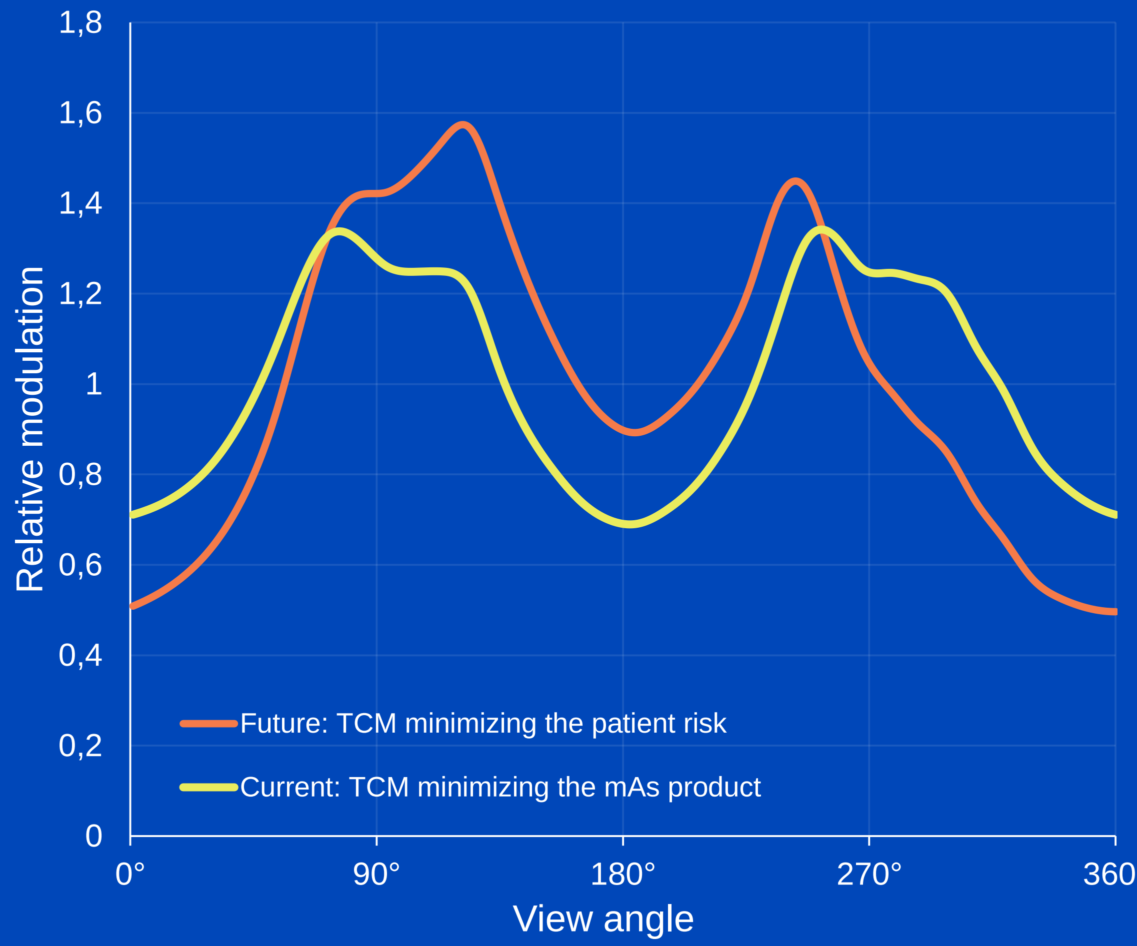




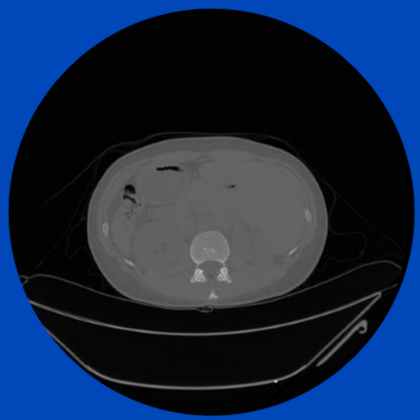
Modulation Curves 150 kV

Angular modulation, nz = 10

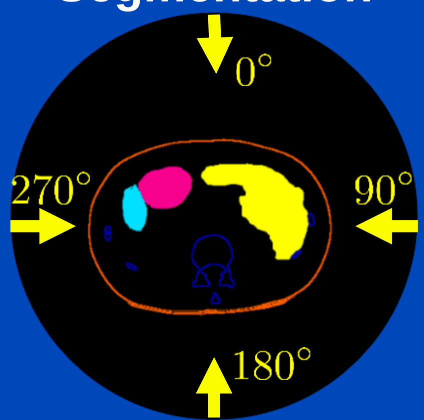
Organ / weight

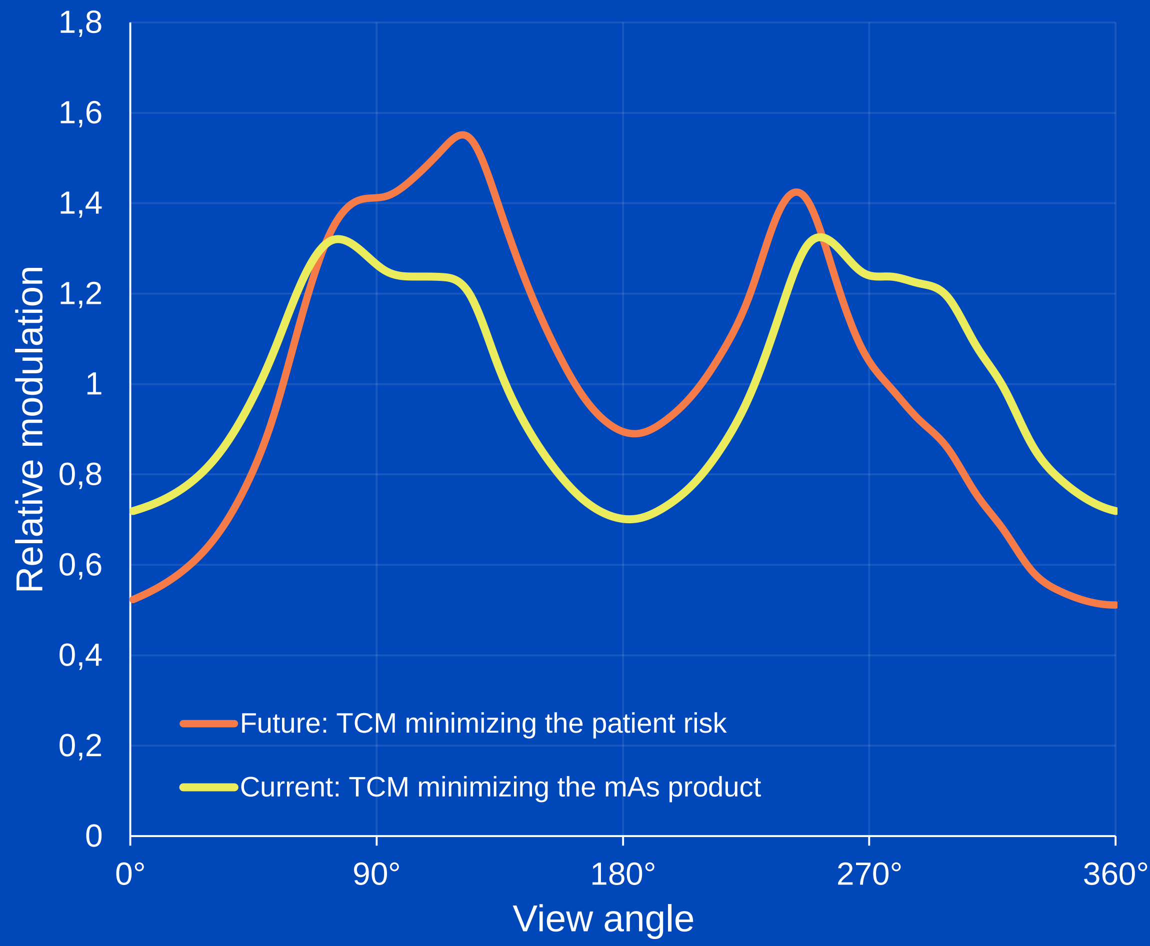
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation





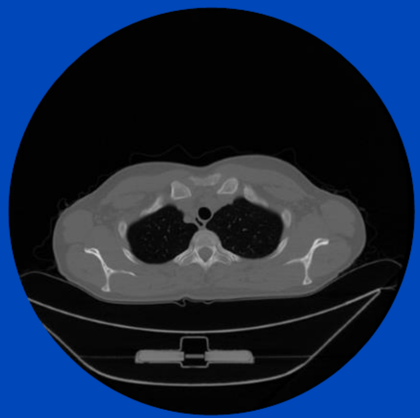
Modulation Curves 70 kV

Angular modulation, nz = 18

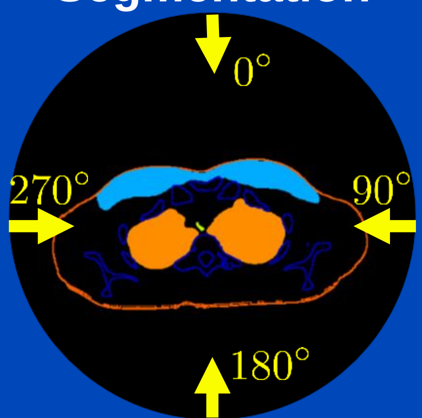
Organ / weight

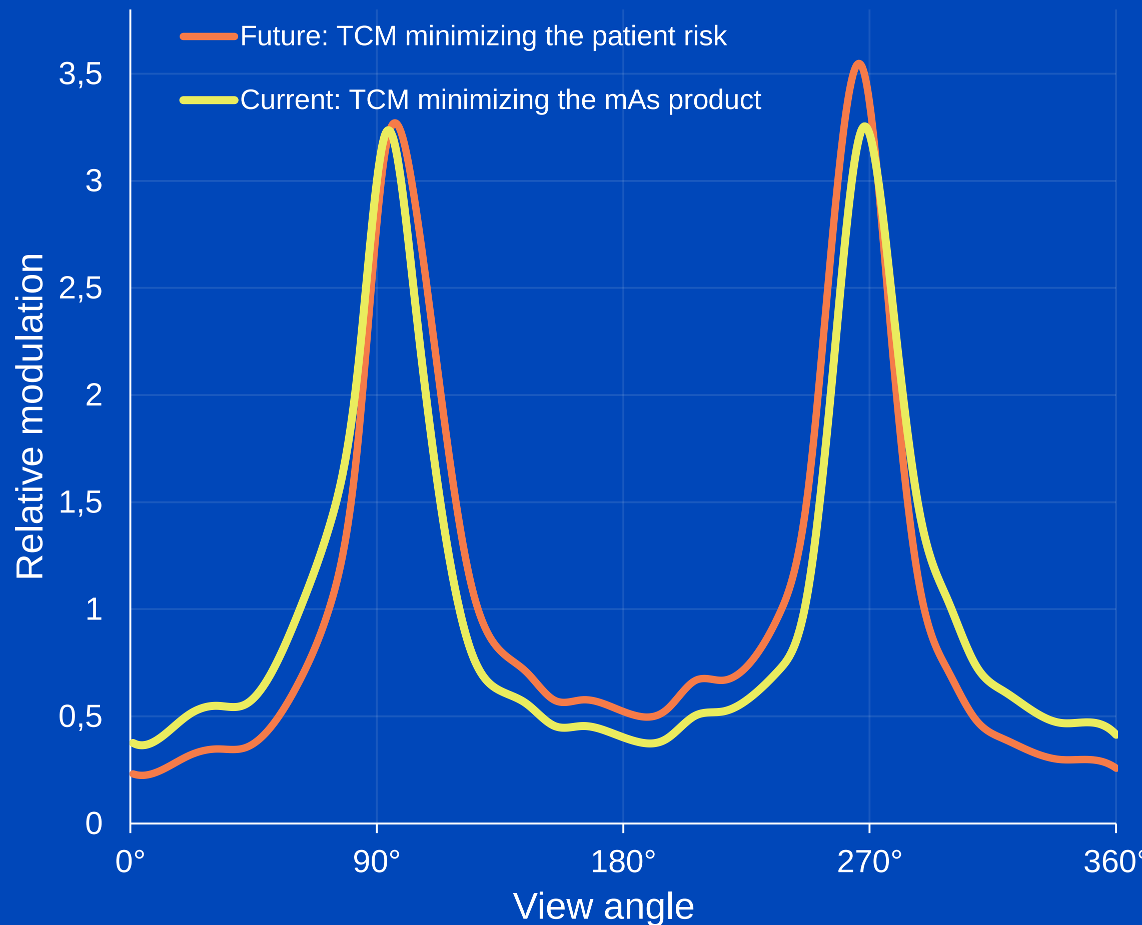
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



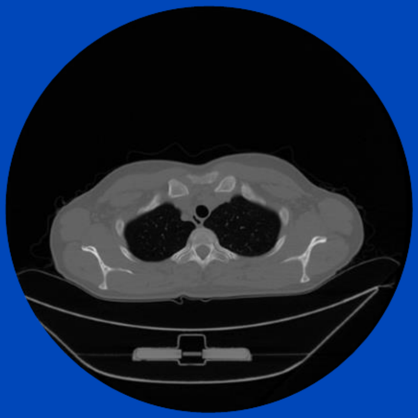


Modulation Curves 120 kV

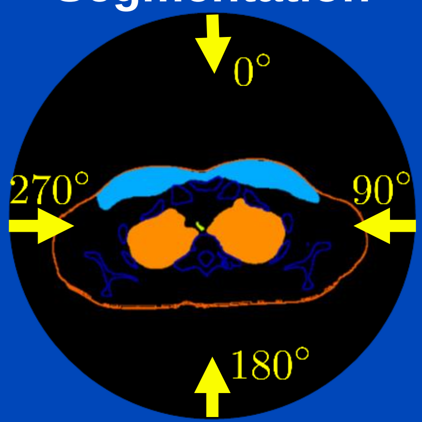
Angular modulation, nz = 18

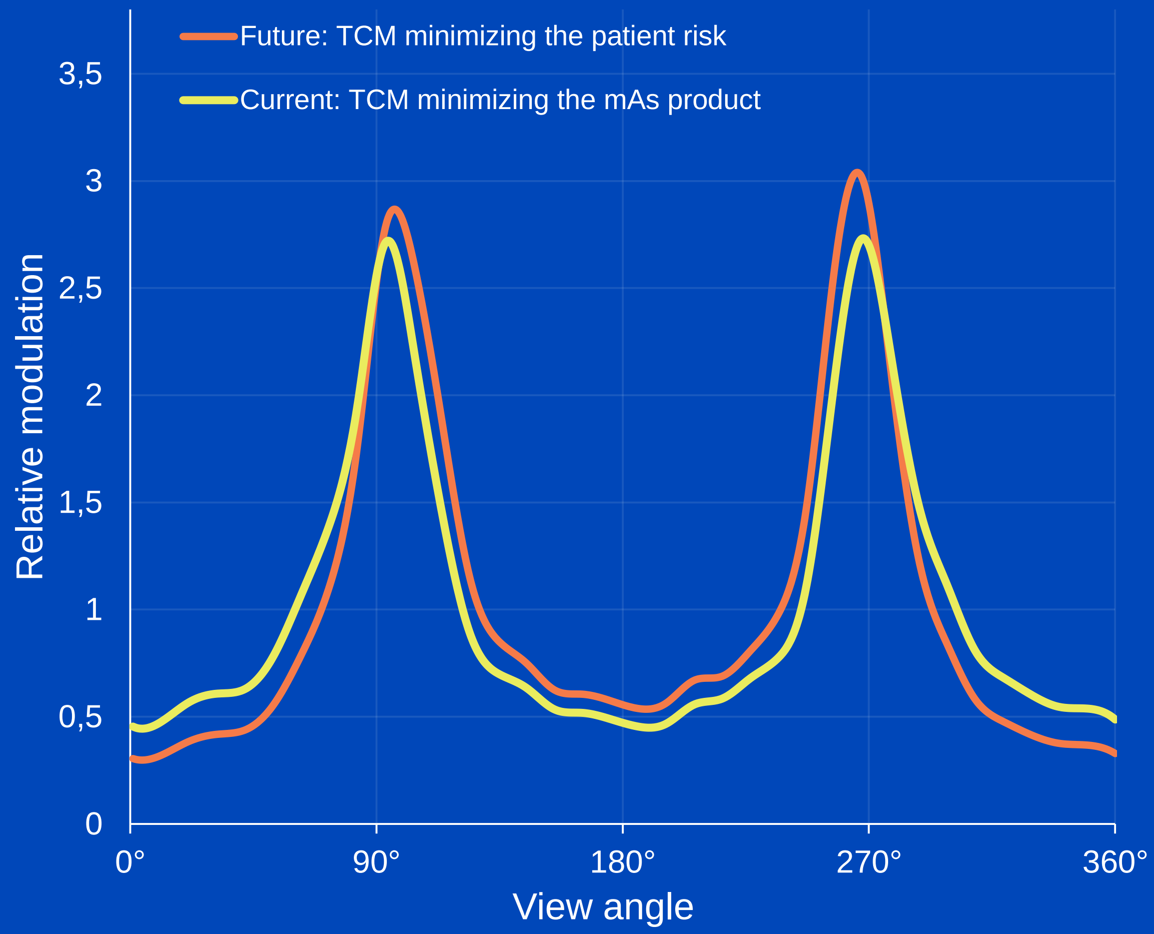
Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image



Segmentation



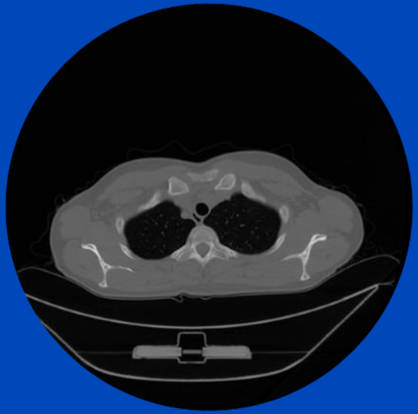


Modulation Curves 150 kV

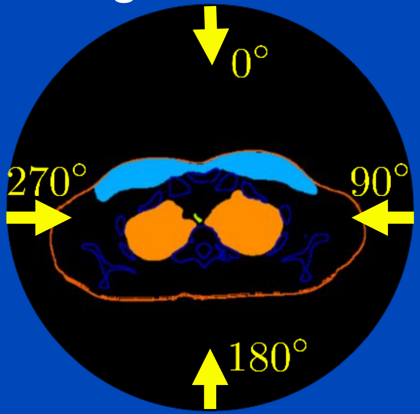
Angular modulation, nz = 18

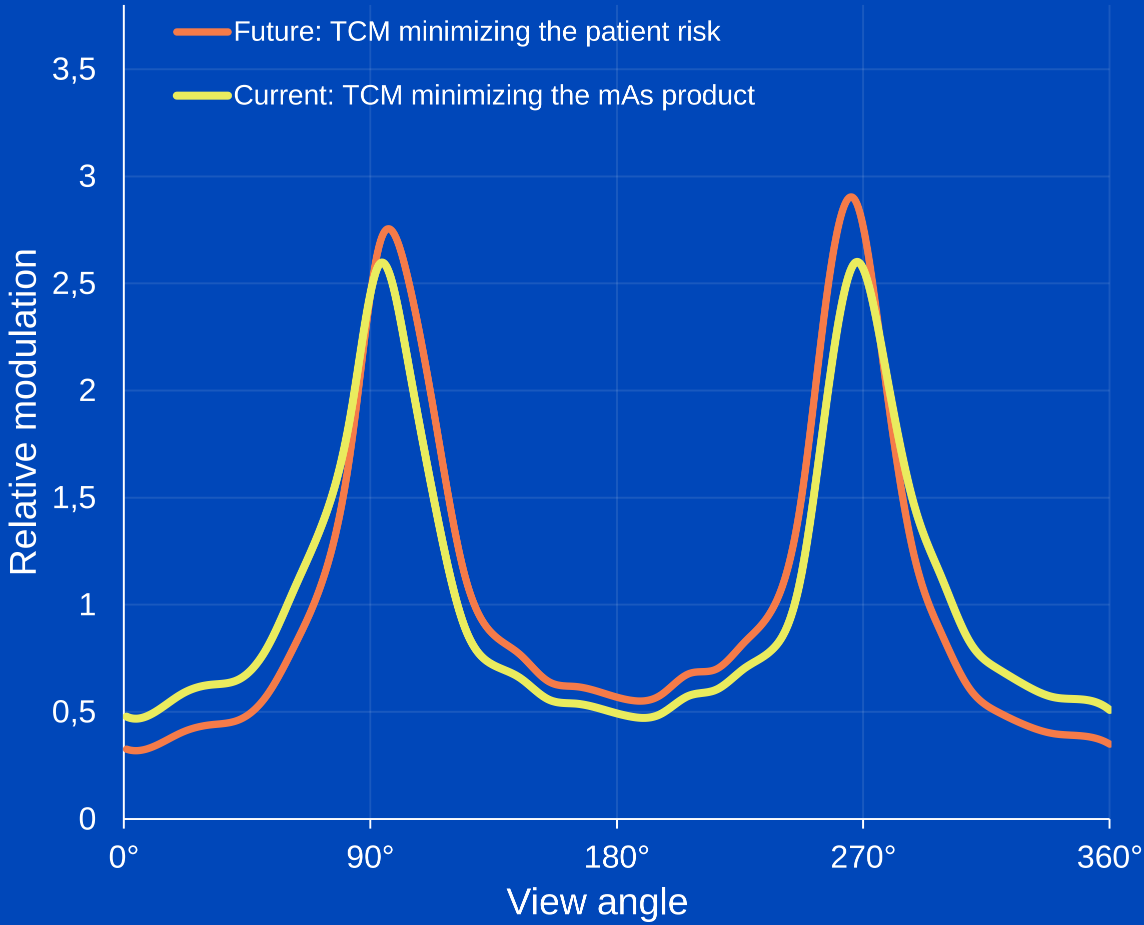
Organ / weight
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Thyroid 0.04
Bladder 0.04

CT image

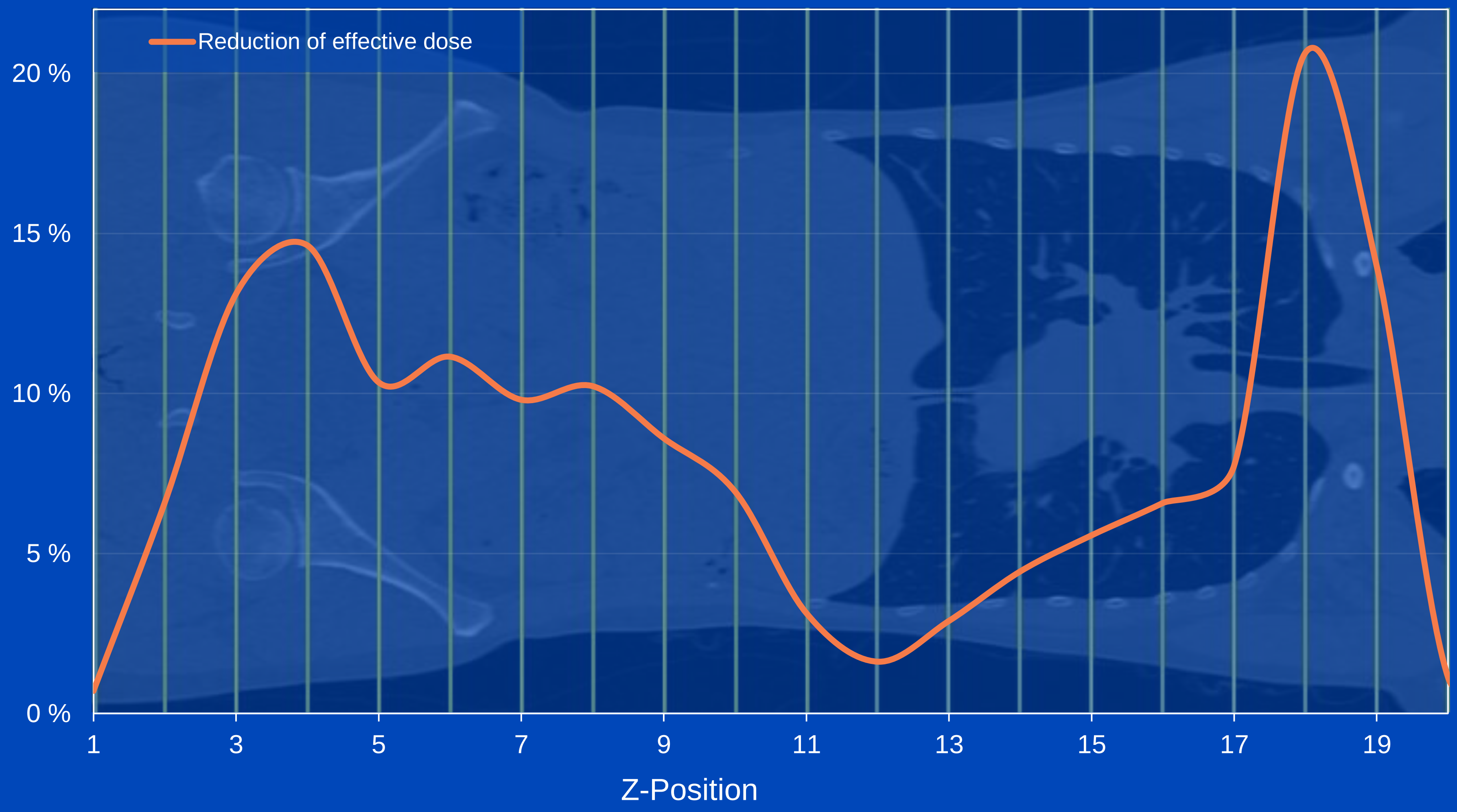


Segmentation



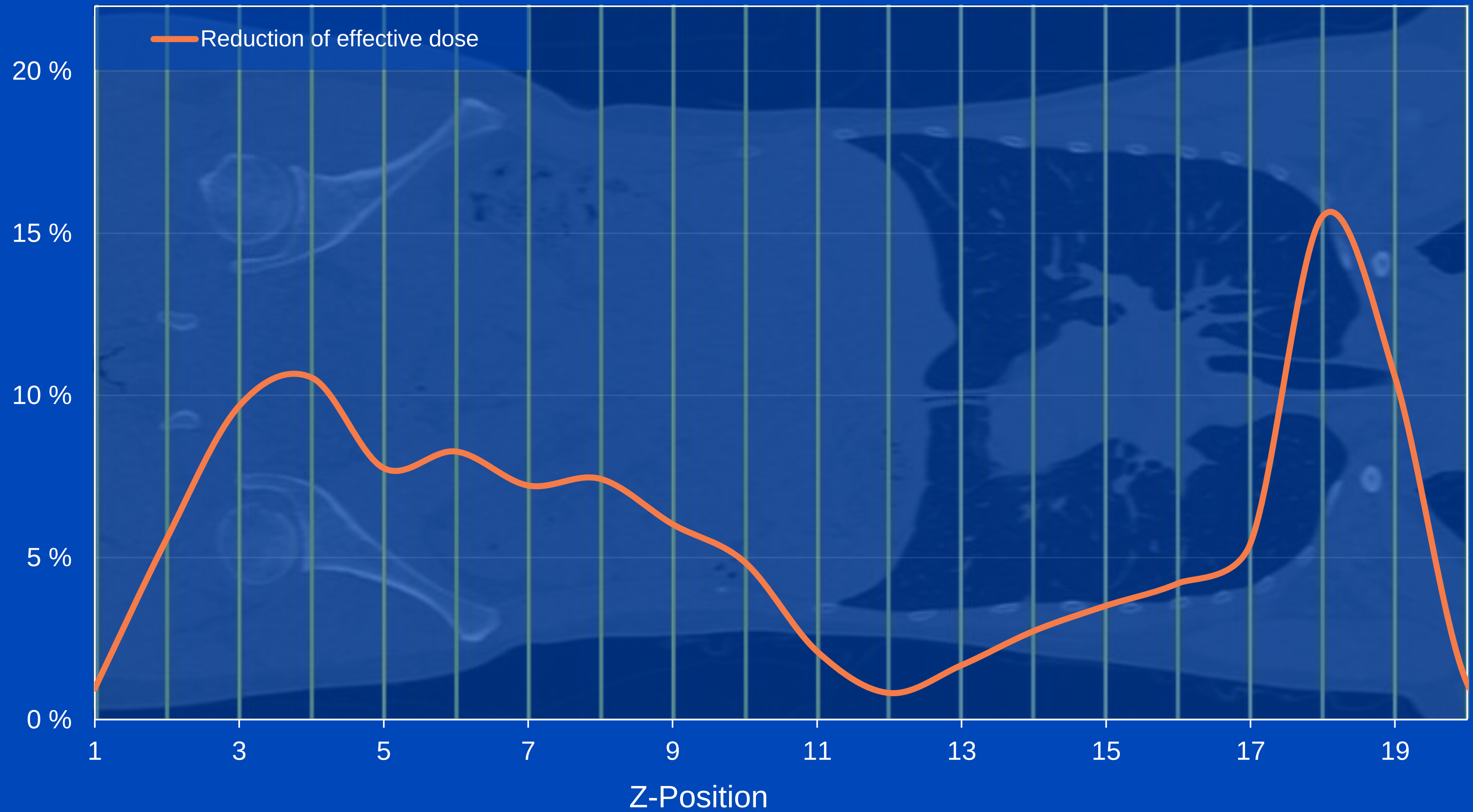


Reduction of Effective Dose 70 kV



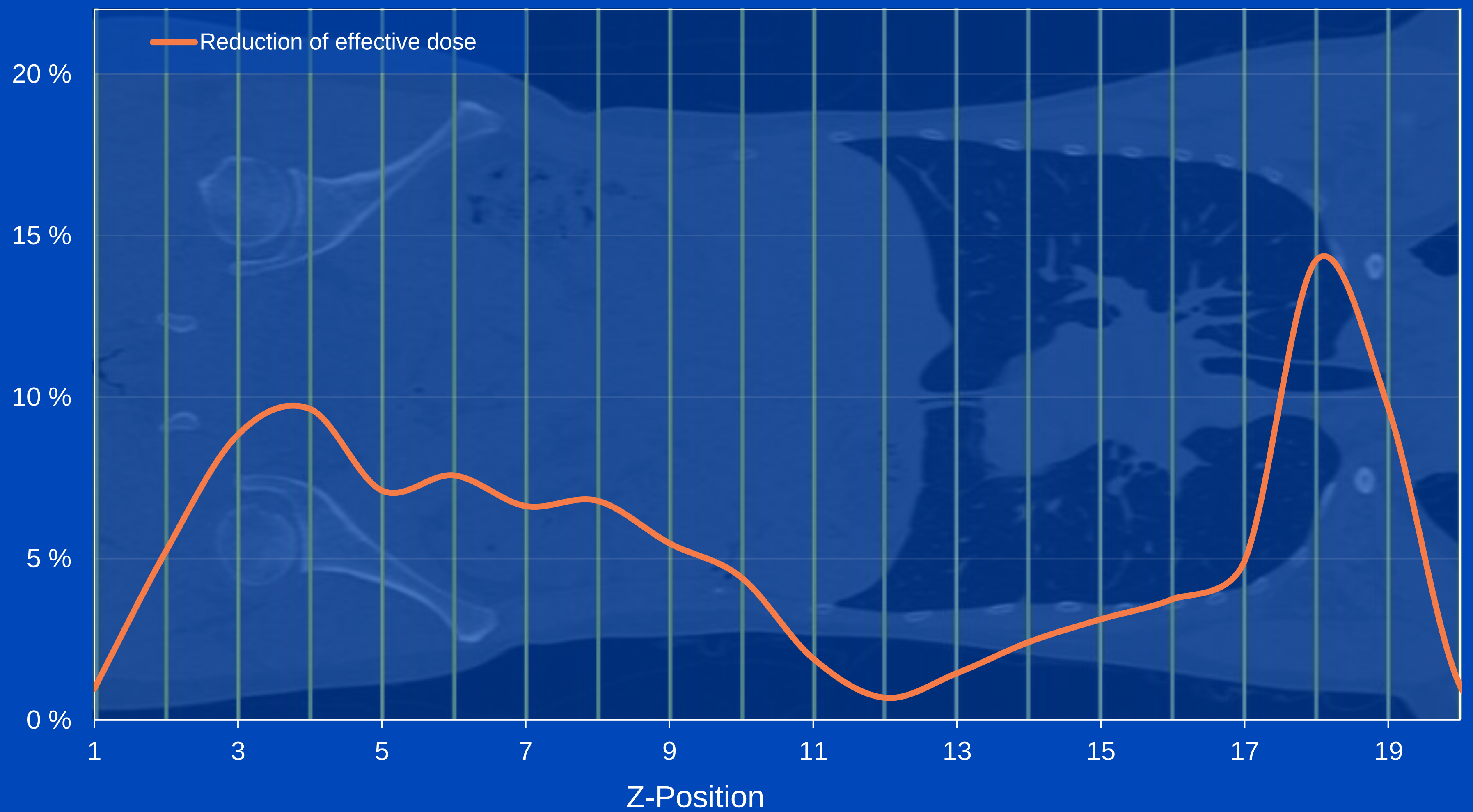
→ **Reduction of the effective dose for the complete scan: 11.5 %**

Reduction of Effective Dose 120 kV



→ **Reduction of the effective dose for the complete scan: 7.5 %**

Reduction of Effective Dose 150 kV



→ **Reduction of the effective dose for the complete scan: 6.6 %**

dkfz.

Conclusions

- Current AEC systems can reduce the dose by 35 % - 60 % while maintaining image quality[1].
- Deep learning-based approaches may open new options for AEC.
- Here, the potential of a tube current modulation that minimizes the radiation risk instead of the mAs product was investigated.
- Compared to a conventional tube current modulation, the effective dose could be further reduced by about 11.5 %, 7.5 %, and 6.6 % for 70 kV, 120 kV and 150 kV, respectively.

[1] M. Söderberg, M. Gunnarsson, Acta Radiologica 51 (6): 625–634 (2010).

Thank You!

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