Projection-based CBCT correction using Monte Carlo simulations and deep convolutional neural networks for adaptive head and neck proton therapy

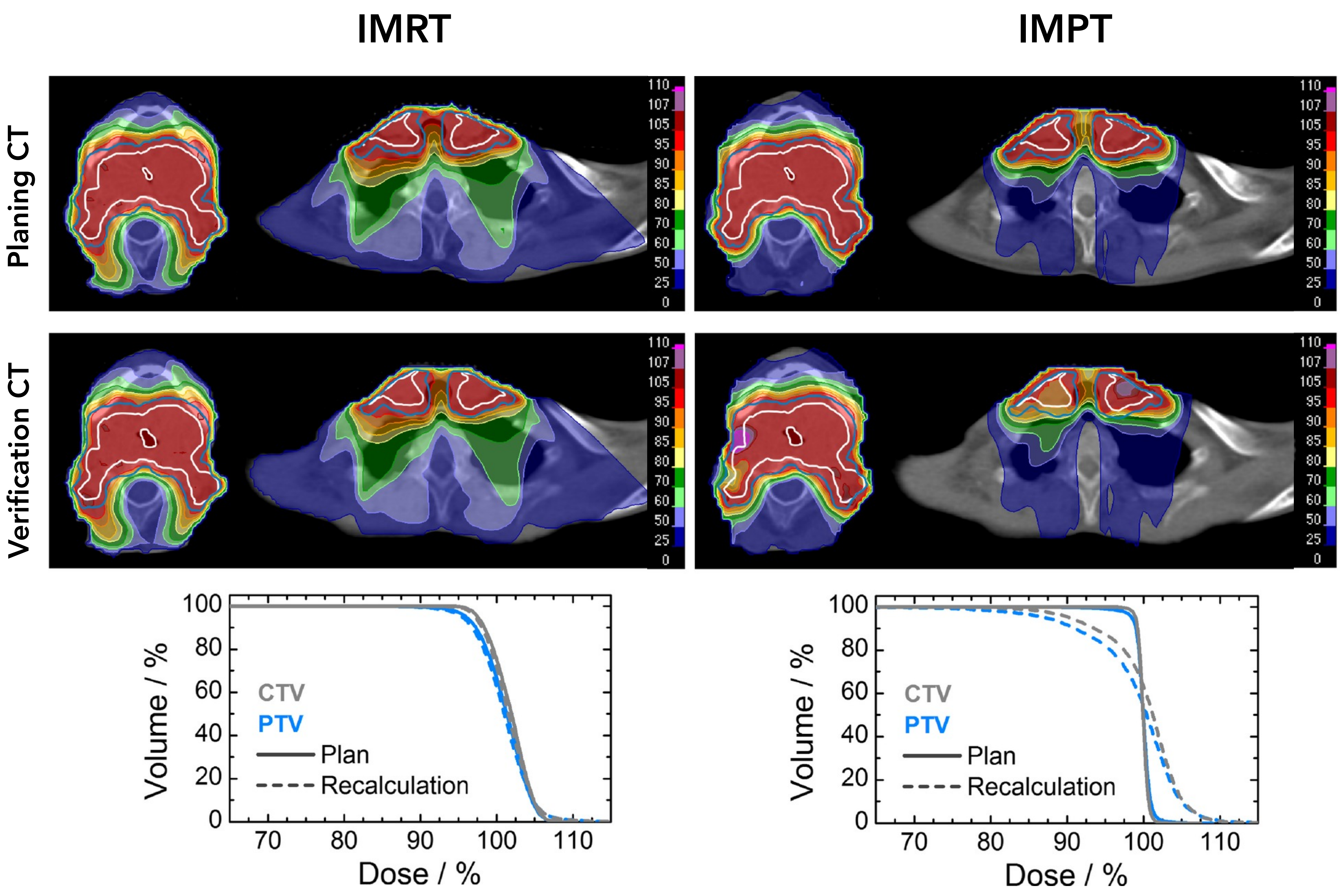
A Lalonde, B Winey, J Verburg, H Paganetti, G Sharp
Department of Radiation Oncology, Massachusetts General Hospital & Harvard Medical School, Boston, MA, USA.

HARVARD MEDICAL SCHOOL

MGH 1811 MASSACHUSETTS GENERAL HOSPITAL

ADAPTIVE PROTON THERAPY

- Intensity-modulated proton therapy (**IMPT**) can **spare** more organs at risk than **IMRT** for head and neck patients[1].
- Anatomical **changes** and set-up **variations** can severely **impair** treatment **quality**.[2]
    - Solution: **Adaptive proton therapy (APT)**.

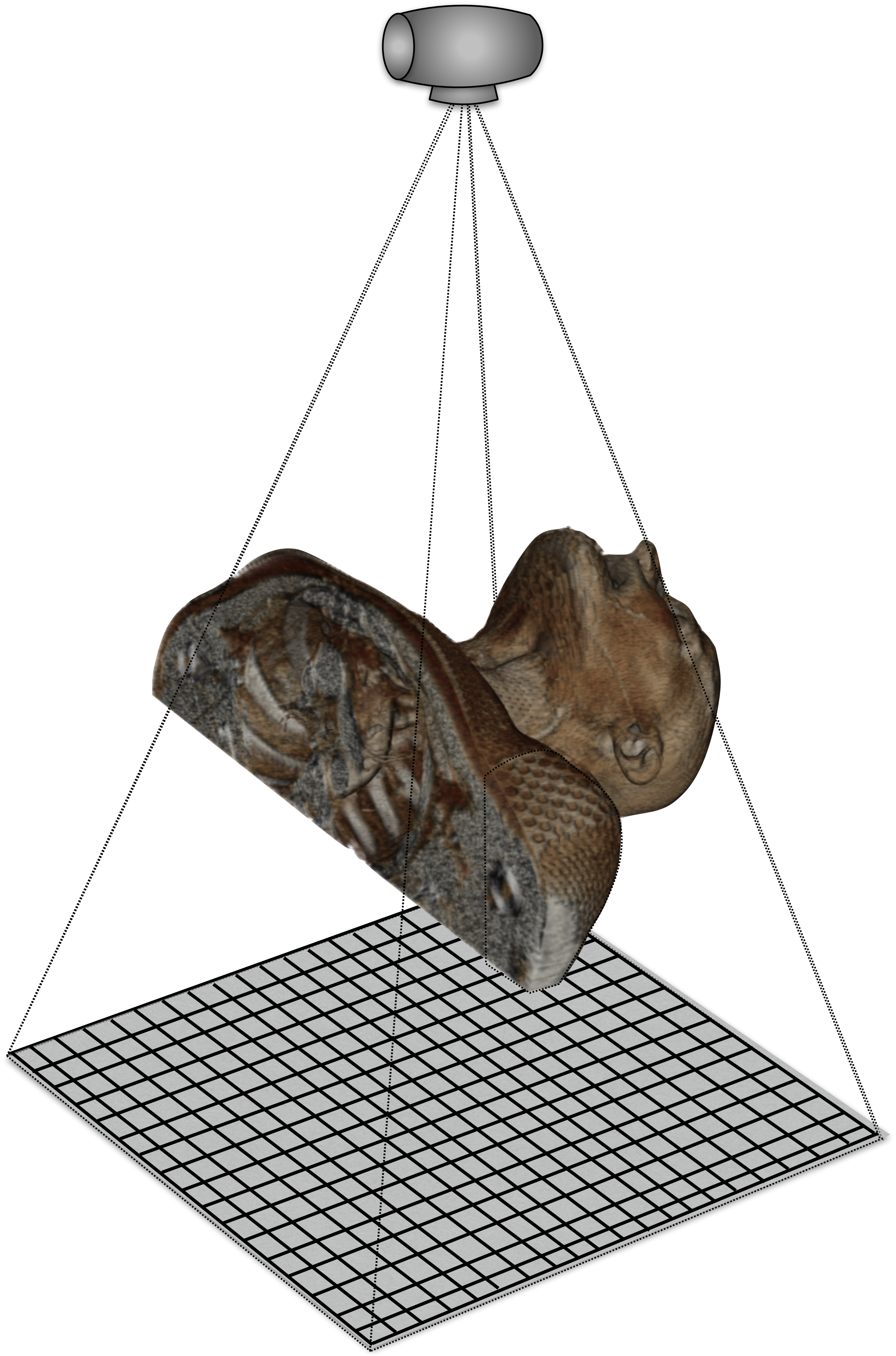


[1] Barten, Danique LJ, et al. "Comparison of organ–at–risk sparing and plan robustness for spot–scanning proton therapy and volumetric modulated arc photon therapy in head–and–neck cancer." *Med. Phys.* 42.11 (2015): 6589-6598.

[2] Stützer, Kristin, et al. "Potential proton and photon dose degradation in advanced head and neck cancer patients by intratherapy changes." Journal of applied clinical medical physics 18.6 (2017): 104-113.

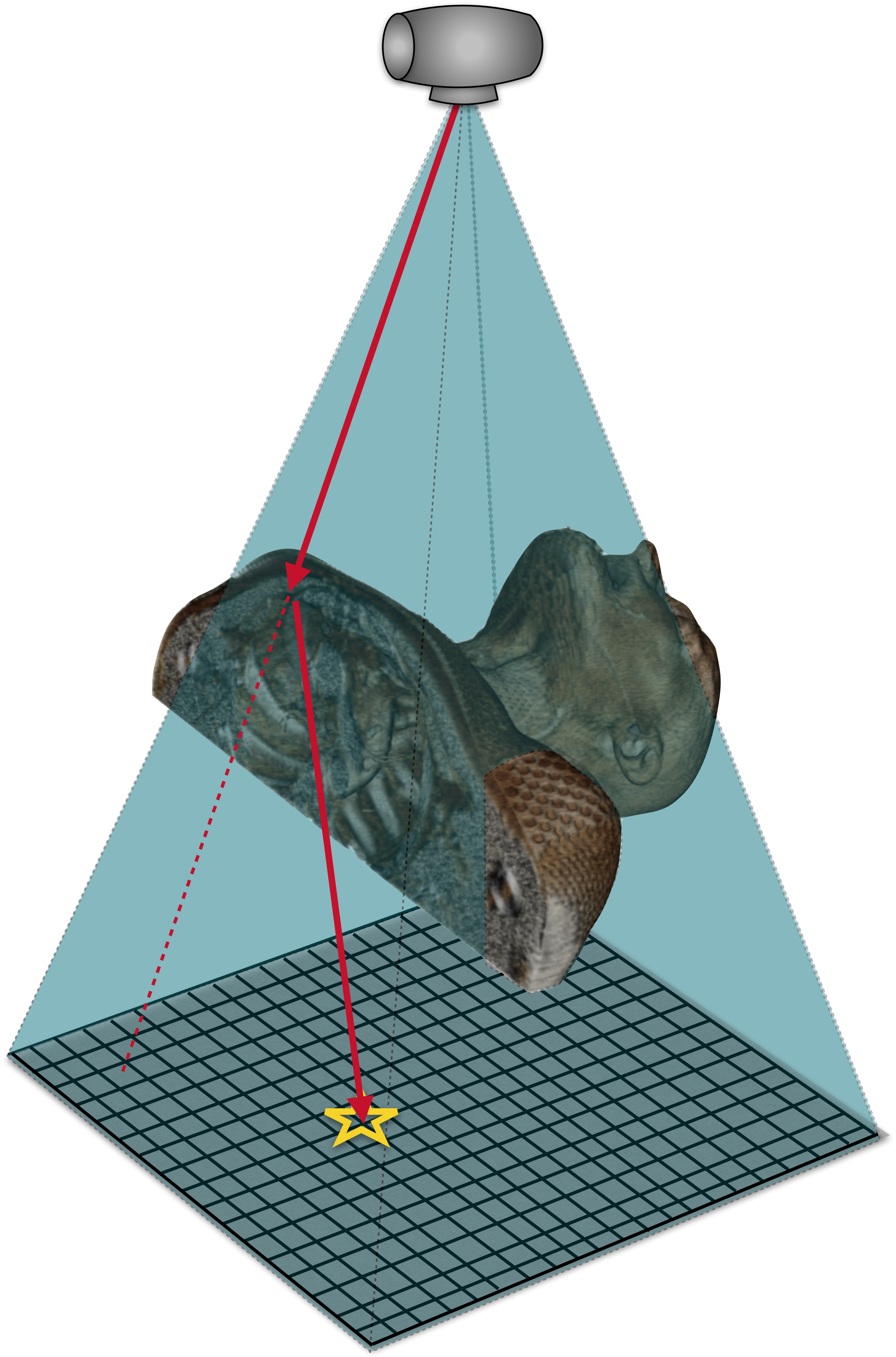
CBCT IMAGING

- Daily **volumetric** imaging is needed for online APT.
  - Cone-beam CT (**CBCT**) is readily available in several proton therapy centers



CBCT IMAGING

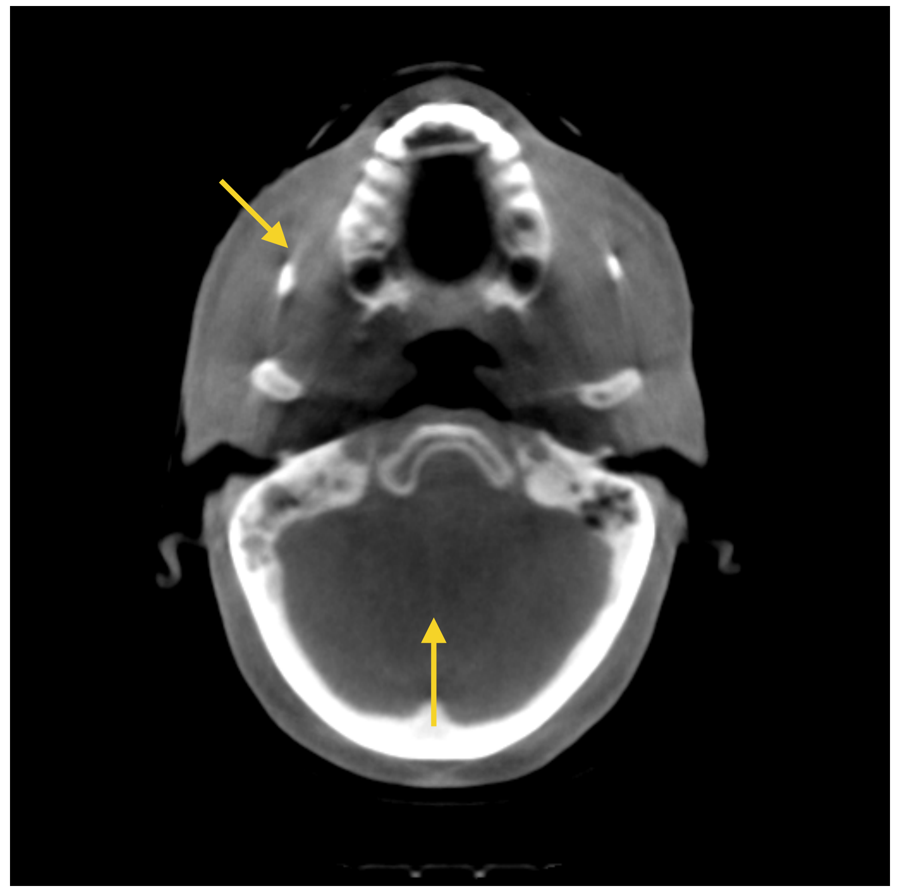
- Daily **volumetric** imaging is needed for online APT
  - Cone-beam CT (**CBCT**) is readily available in several proton therapy centers
- X-ray **scatter** in patient anatomy generates **artifacts** in CBCT projections



CBCT IMAGING

- Daily **volumetric** imaging is needed for online APT
  - Cone-beam CT (**CBCT**) is readily available in several proton therapy centers
- X-ray **scatter** in patient anatomy generates **artifacts** in CBCT projections
- Scatter artifacts severely affect **image quality** and make accurate proton dose calculation **impossible**

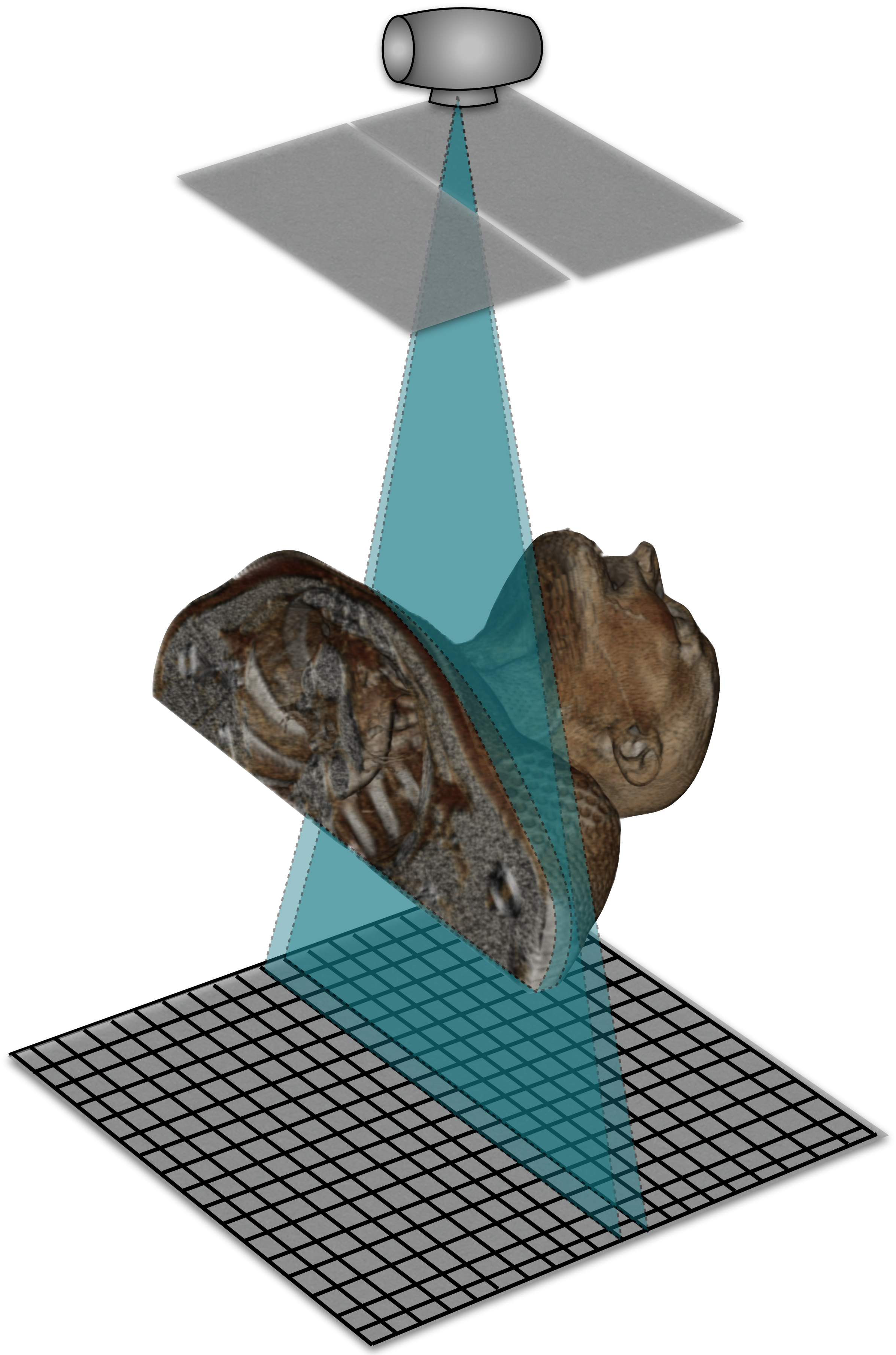
Uncorrected



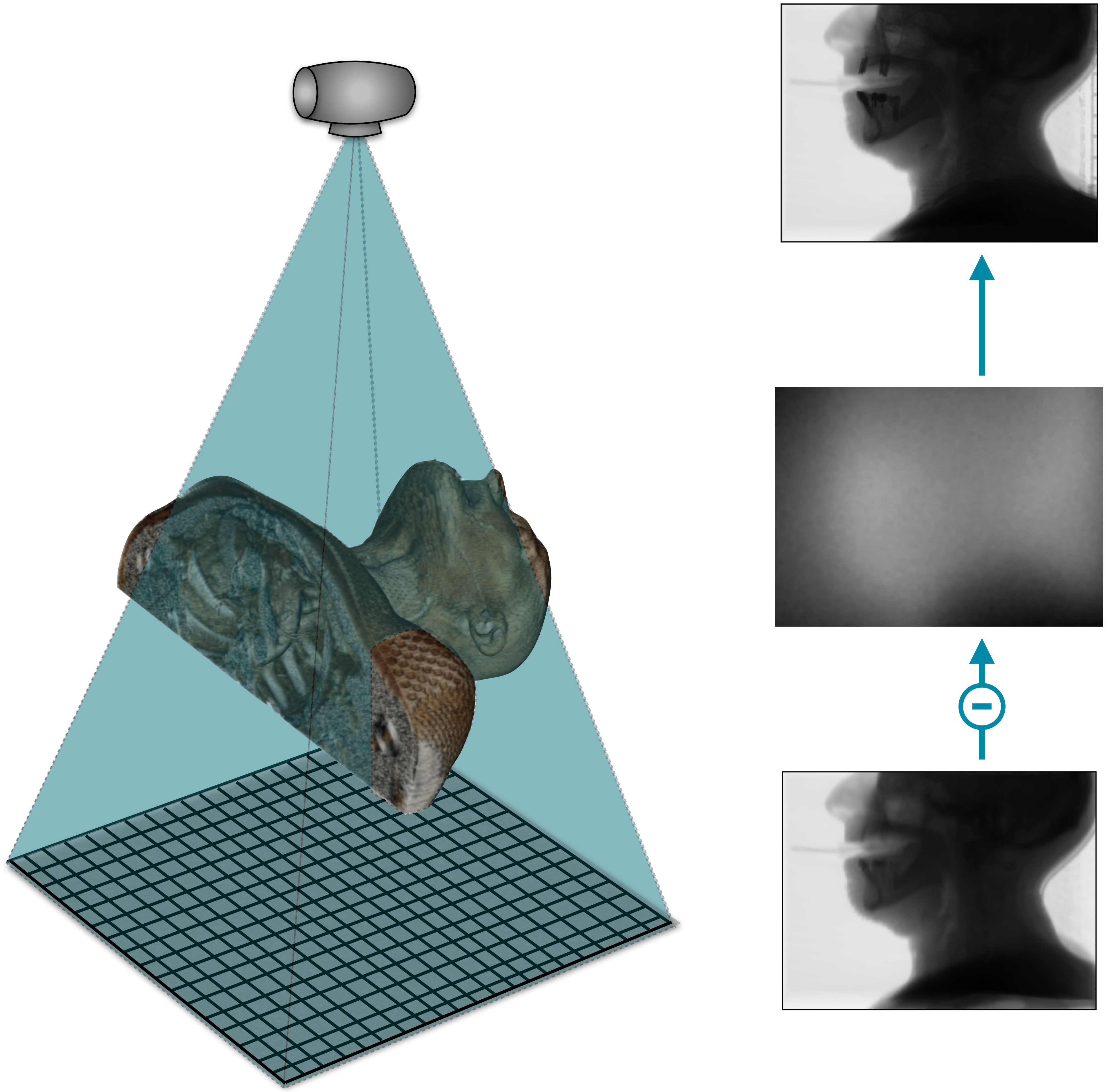
Scatter free

SCATTER CORRECTION

Scatter rejection



Scatter subtraction



SCATTER SUBTRACTION

- Monte Carlo (**MC**) simulations have been shown to be the most **accurate** scatter subtraction approach.
  - Too **computationally demanding** for real-time usage in APT.[1]

- Recent work have shown that scatter estimation can be substantially **accelerated** using deep convolutional **neural networks**.[2,3]

[1] Rührnschopf and, E. P., & Klingenbeck, K. (2011). A general framework and review of scatter correction methods in cone beam CT. Part 2: scatter estimation approaches. Medical physics, 38(9), 5186-5199.

[2] Hansen, David C., et al. "ScatterNet: A convolutional neural network for cone−beam CT intensity correction." *Medical physics* 45.11 (2018): 4916-4926.

[3] Maier, Joscha, et al. "Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network." *Journal of Nondestructive Evaluation* 37.3 (2018): 57.

(SOME) RECENT WORK

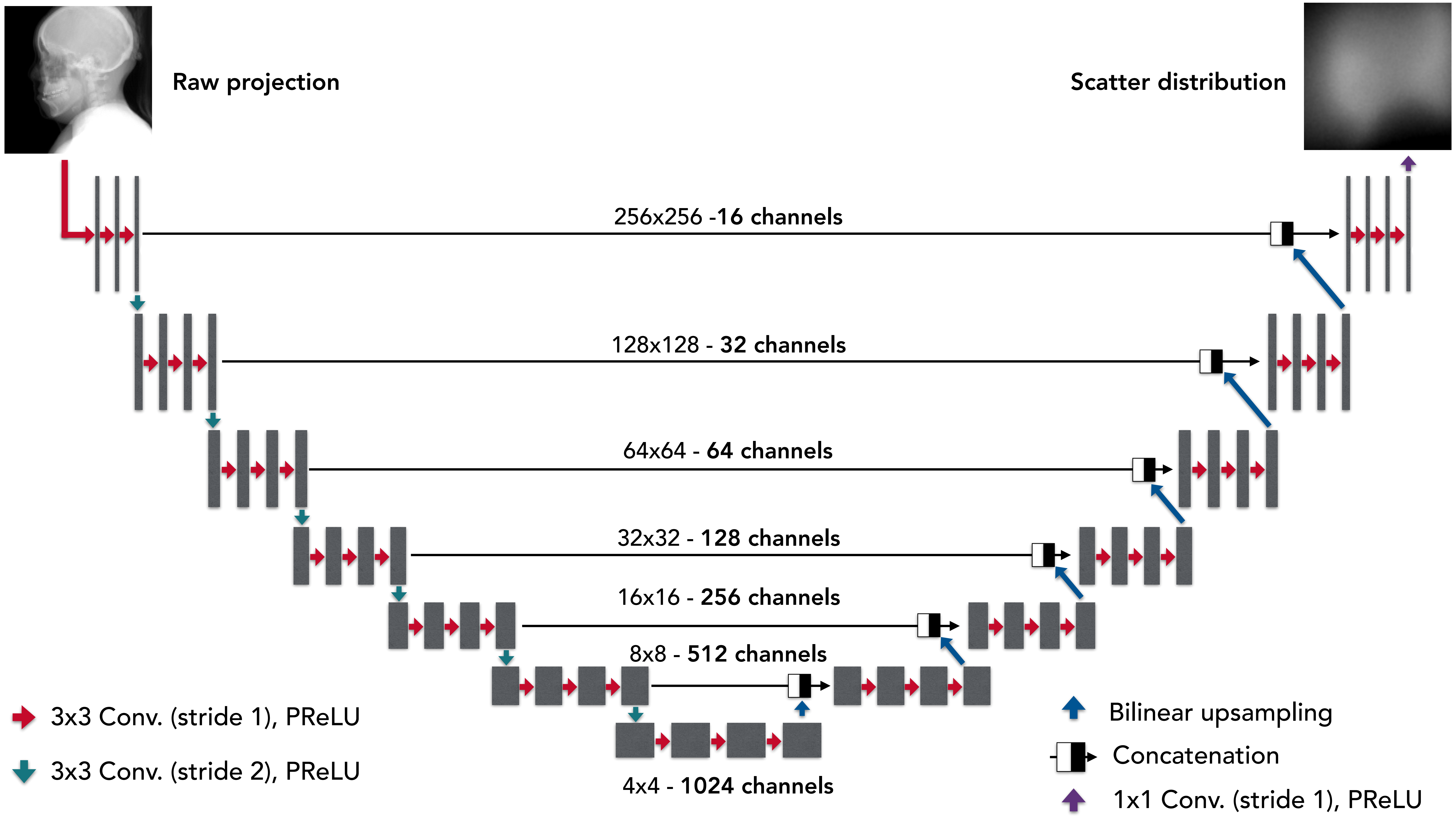
- Hansen *et al*. (Med. Phys 2018): **Projection-based** correction using a **U-Net** trained on **empirically corrected** data.
  - Tested on **pelvis patients**: High accuracy for VMAT dose calculation, **limited accuracy** for **IMPT**.
- Kurz *et al*. (PMB 2019): **Image-based** correction using a **Cycle-GAN** trained on **empirically corrected** data.
  - Tested on **pelvis patients**: High accuracy for VMAT dose calculation, **limited accuracy** for **IMPT**.
- Maier *et al*. (Med. Phys. 2019): **Projection-based** correction using a **U-Net** trained on **Monte Carlo** data
  - High **HU accuracy** on simulated and phantom images, **no dose calculation** performed.

PURPOSE

The purpose of this work is to evaluate the performance of a deep convolutional **neural network** trained on **Monte Carlo** data to provide **fast** and **accurate** CBCT scatter-correction in the context of head and neck **adaptive proton therapy**.

U-NET ARCHITECTURE

- We used a U-Shape deep convolutional neural network (**U-net**)[1] made of **7** layers with **16** to **1024** feature channels[2].
- Input projections are downsampled to **256 x 256**.
- The Unet is trained for **150** epochs.



[1] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

[2] Maier, Joscha, et al. "Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network." *Journal of Nondestructive Evaluation* 37.3 (2018): 57.

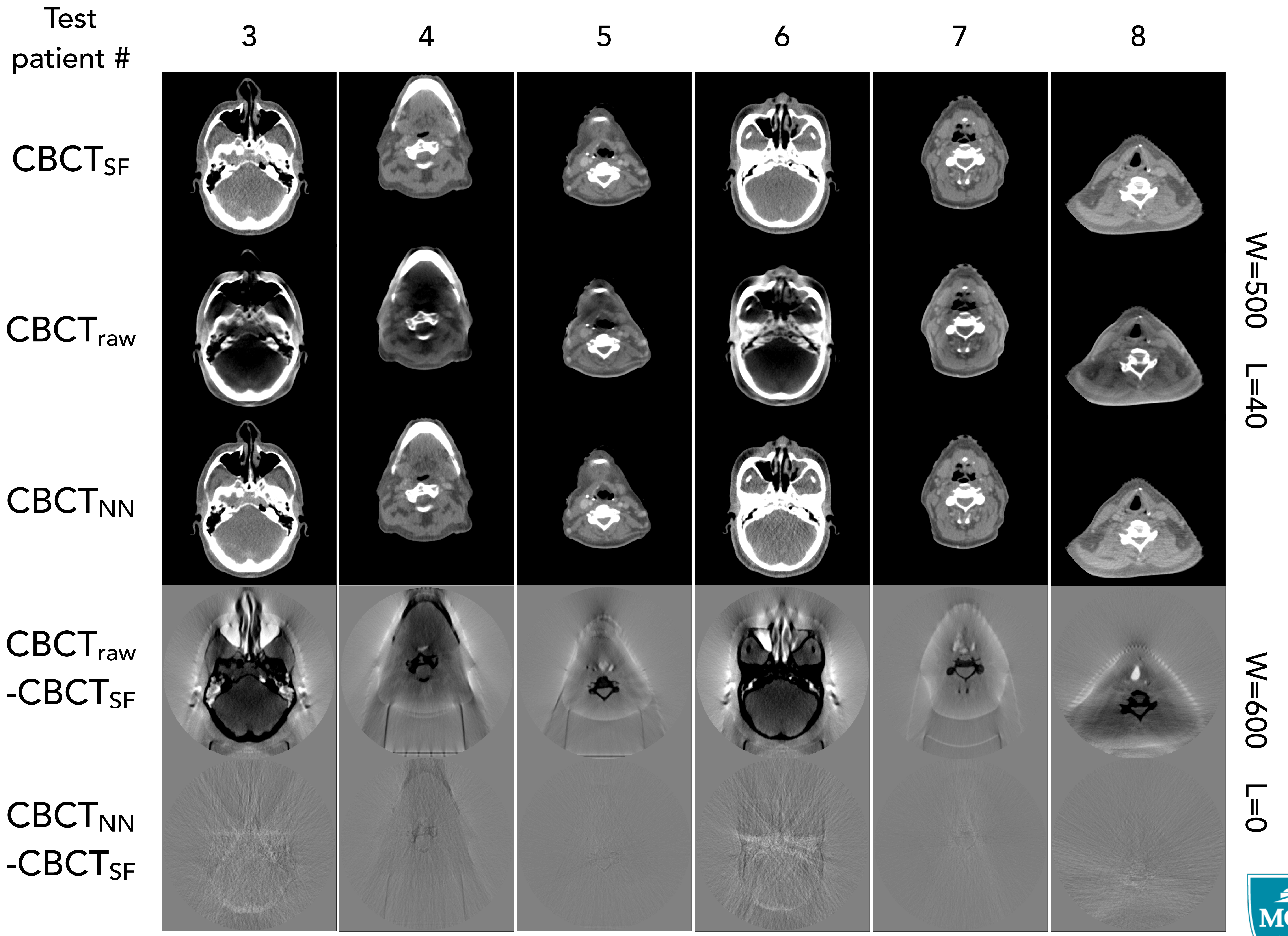
MONTE CARLO SIMULATIONS

- CBCT projections are simulated using the GPU accelerated MC code **MCGPU**.
- The **100 kVp** X-ray spectrum of an Elekta XVI system is modeled using the **SpekCalc**[1] software.
- **48** head and neck patients, distributed in **training** (**29**), **validation** (**9**) and **testing** (**10**) sets are used as input geometry to simulate the CBCT projections.
- A total total of **13,680** pairs of projections are used for **training** and **validation**.

[1] Poludniowski, G., et al. "SpekCalc: a program to calculate photon spectra from tungsten anode x-ray tubes." *Physics in Medicine & Biology* 54.19 (2009): N433.

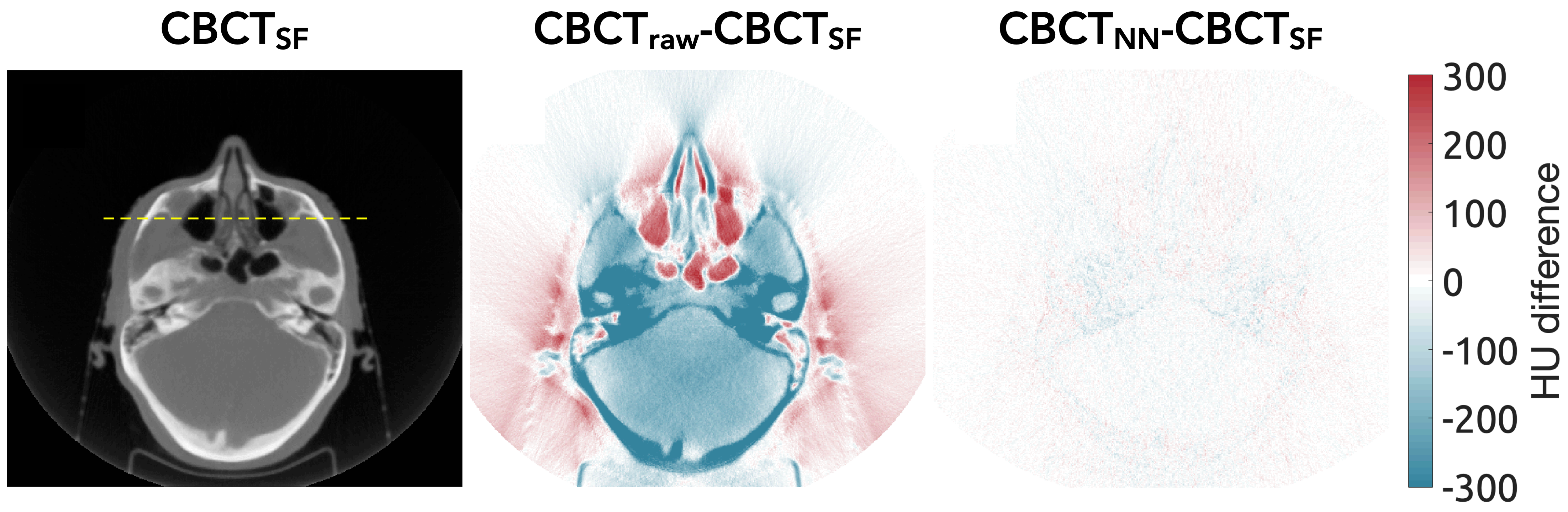
RESULTS

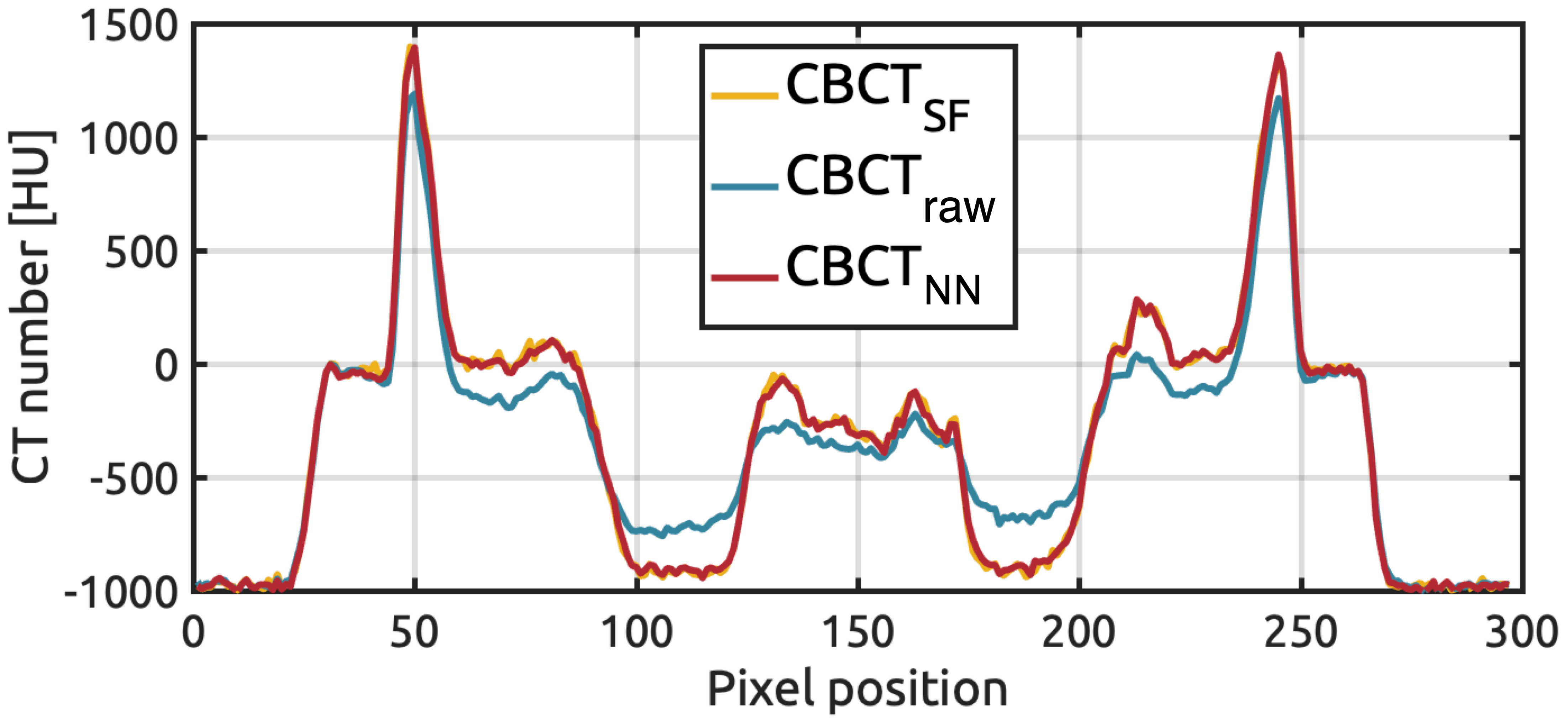
- **$CBCT_{NN}$** yields a substantially **better agreement** with **$CBCT_{SF}$** than **$CBCT_{raw}$**.
- The average computation time per projection is **13.58 ms**.
  - Less than **5 seconds** for a 360 projections volume.



RESULTS - HU ACCURACY

- Almost **perfect agreement** between the HU values in the scatter corrected and scatter free images
- Mean error and mean absolute error on HU error over all test patients of (**-0.8, 13.4**) for **$CBCT_{NN}$** vs (**-28.6, 69.6**) for **$CBCT_{raw}$**





IMPACT OF COST FUNCTION

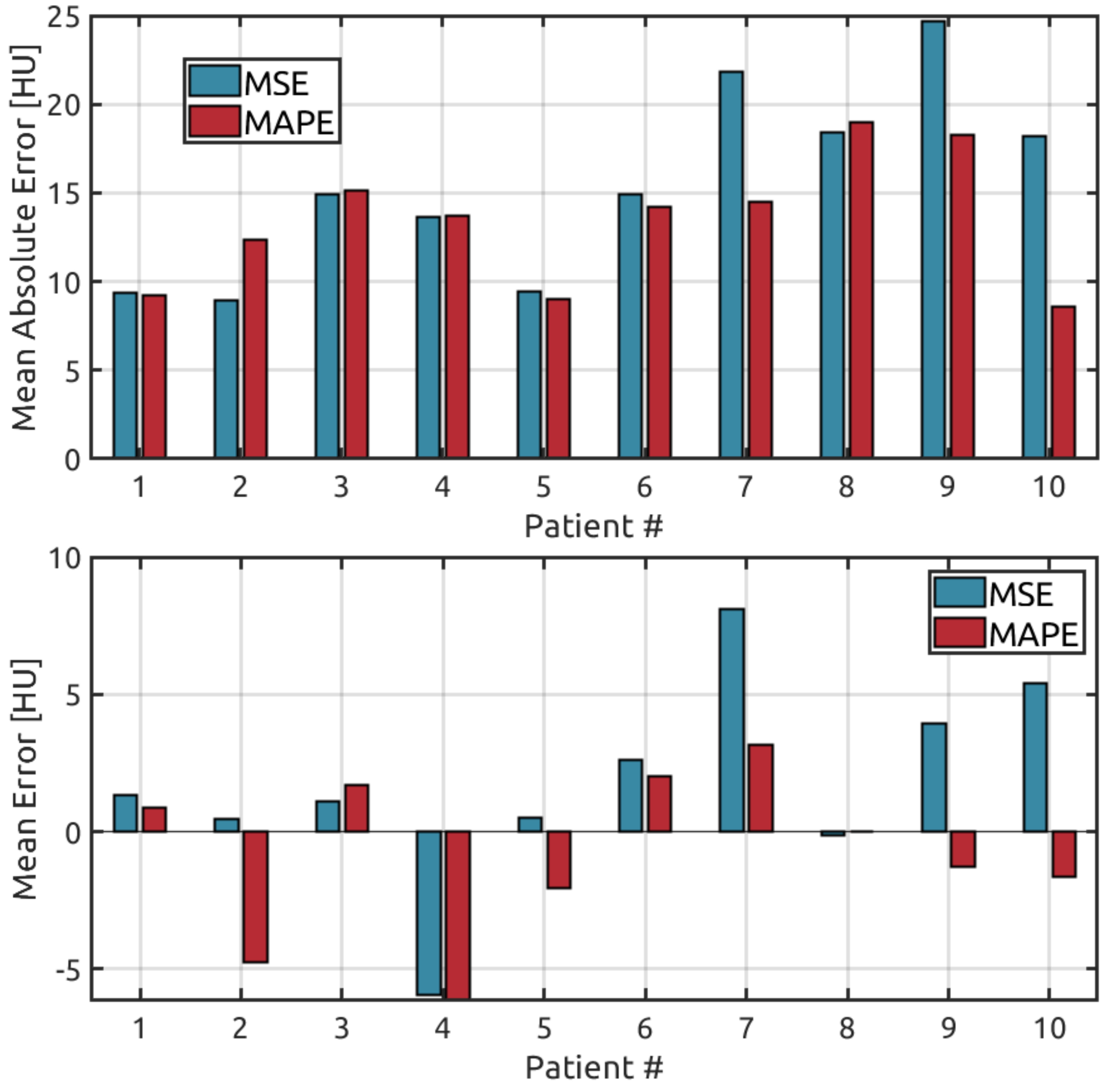
- HU accuracy for two different **cost-functions**:
  - Mean squared error (**MSE**):

$$\frac{1}{N}\sum_{\mathbf{d},n}\left(Unet(\mathbf{d},n,\mathbf{w},\mathbf{b})-S(\mathbf{d},n)\right)^2$$

  - Mean absolute percentage error (**MAPE**):

$$\frac{100}{N}\sum_{\mathbf{d},n}\left|\frac{Unet(\mathbf{d},n,\mathbf{w},\mathbf{b})-S(\mathbf{d},n)}{S(\mathbf{d},n)}\right|$$

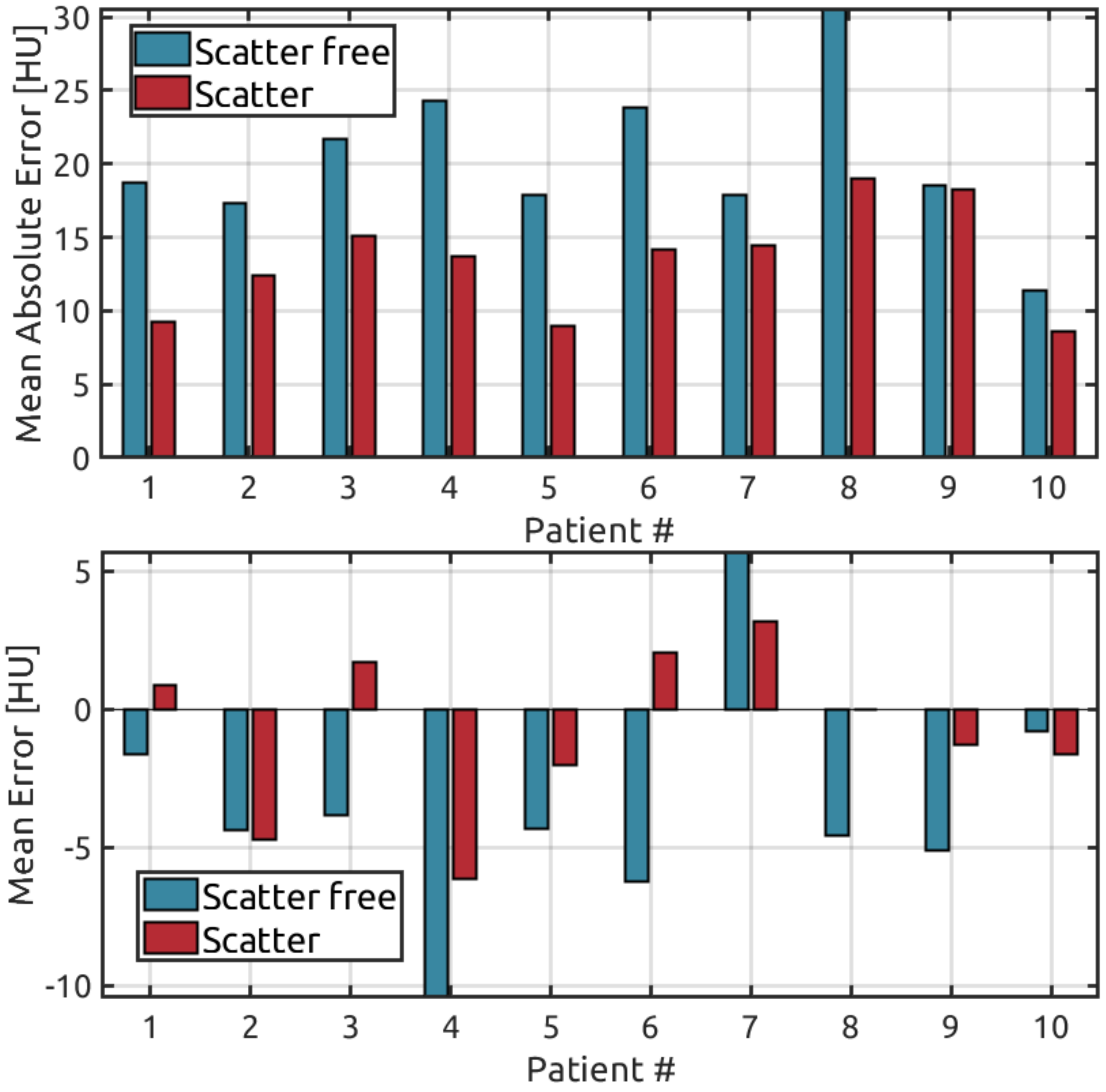
- Best HU accuracy with **MAPE**.



LEARNING SCATTER MAPS VS SCATTER FREE PROJECTIONS

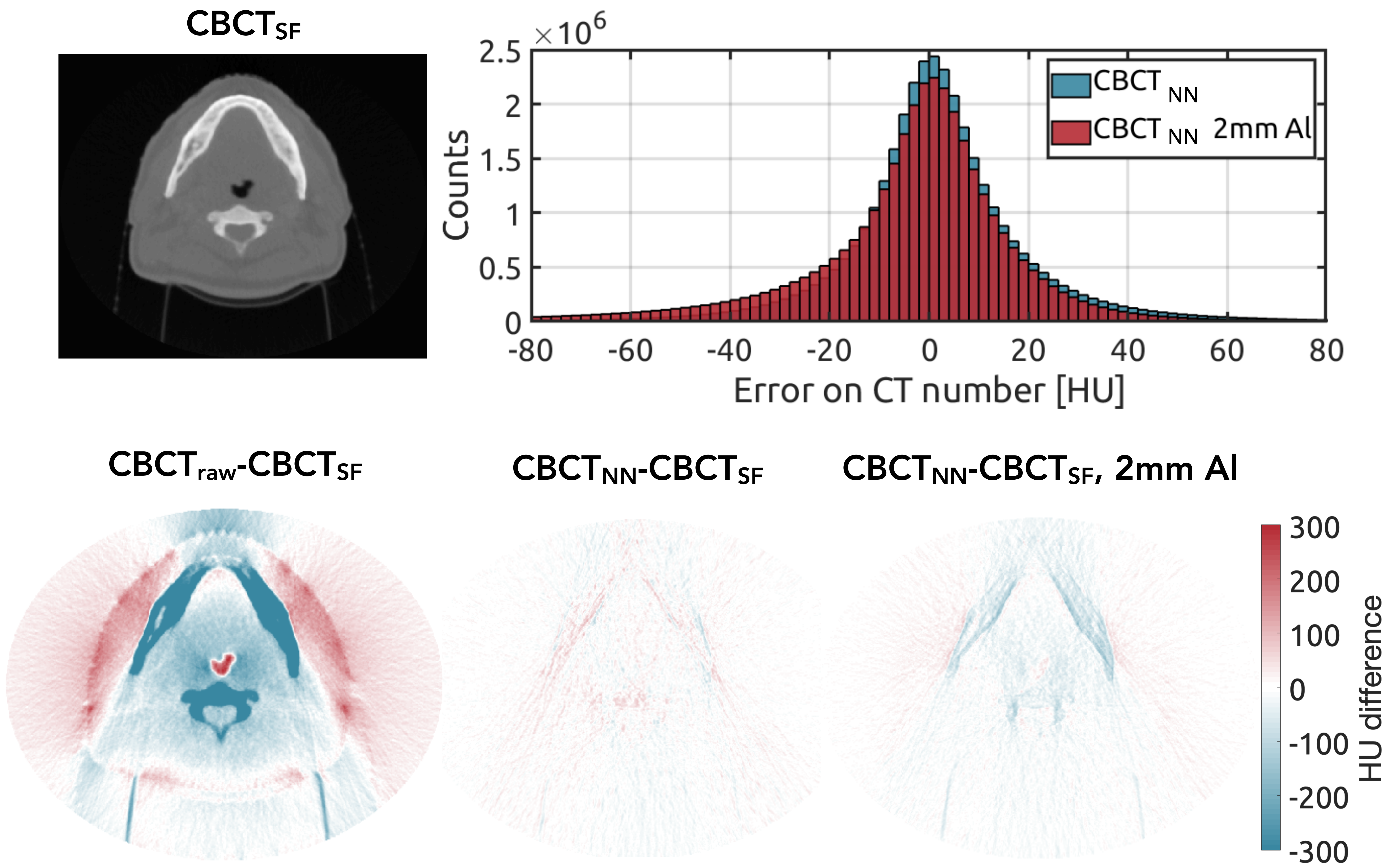
- HU accuracy for two different **target quantities**:
  - Normalized scatter: $p_{raw} \rightarrow s = \frac{S}{I_0}$
  - Scatter free: $p_{raw} \rightarrow p_{SF}$
- Best HU accuracy when learning **Scatter** distributions.

$$p_{raw} = -\ln\left(\frac{I+S}{I_0}\right) \qquad p_{SF} = -\ln\left(\frac{I}{I_0}\right)$$



IMPACT OF SPECTRAL ACCURACY

- Added a **2 mm Al** filtration to the spectra used during training for one of the **validation** patient.
- Some **effect** is observed, but the correction quality is **not** noticeably **impaired**.



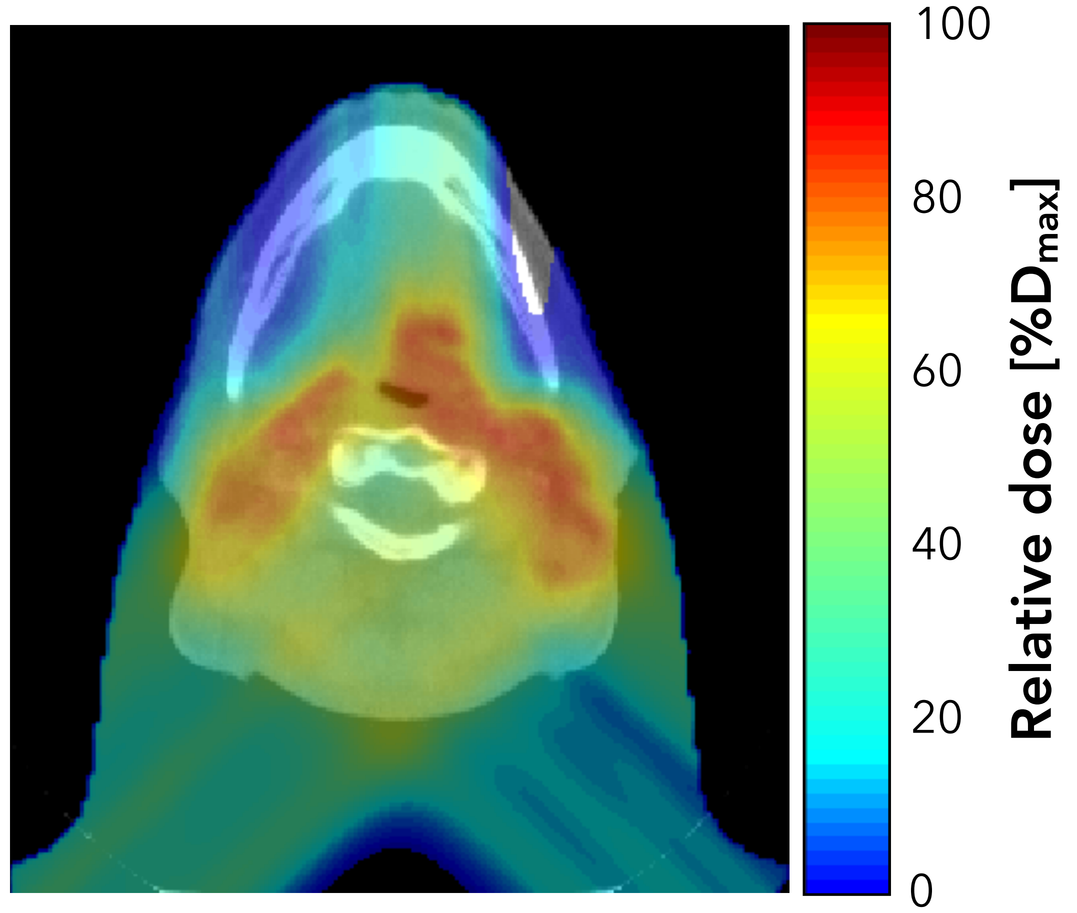
DOSE CALCULATION ACCURACY

- **IMPT** plans are created for the **10 test** patients using RayStation.
- Dose distributions calculated in **$CBCT_{SF}$** are used as **reference** and compared to **$CBCT_{NN}$** and **$CBCT_{raw}$**.

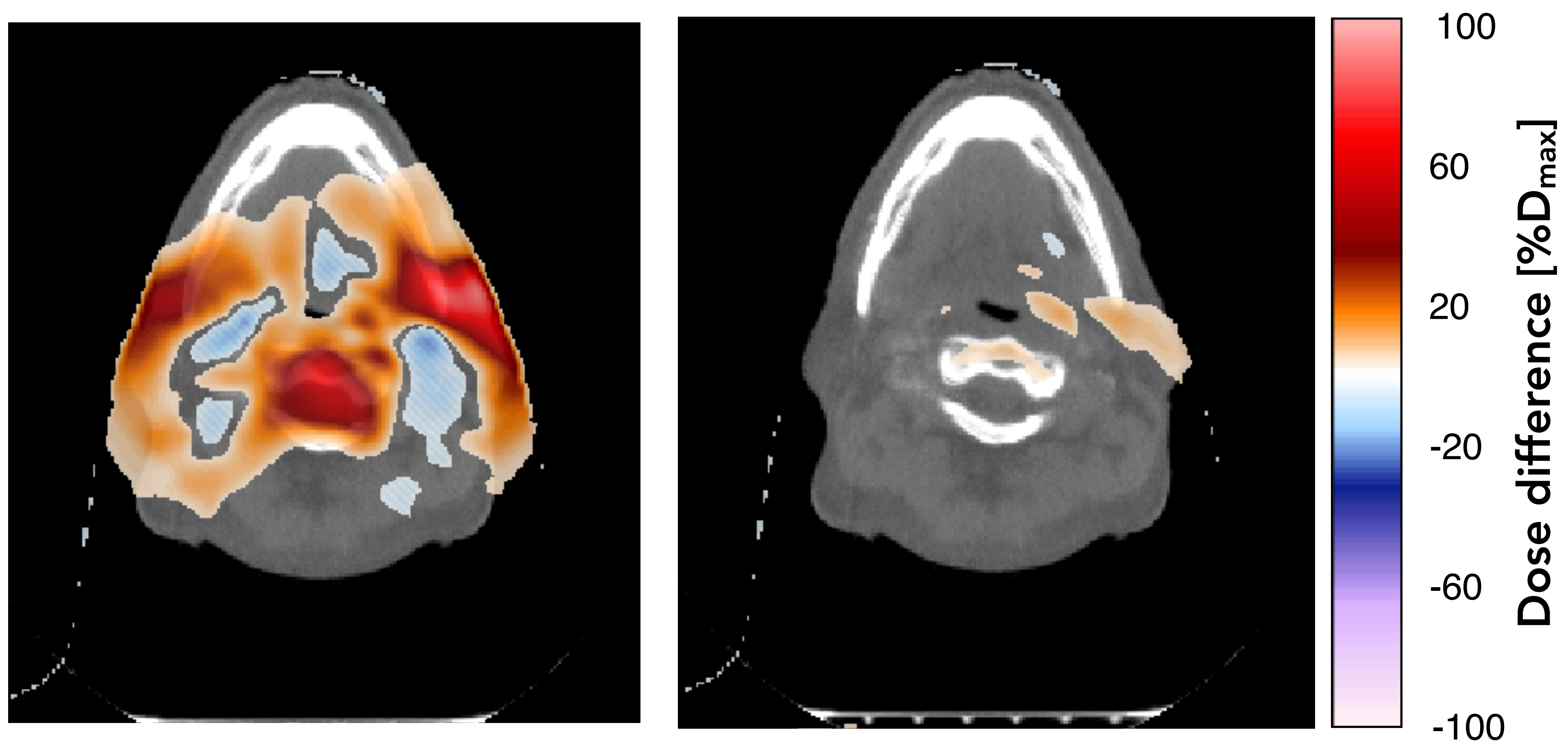
2%/2mm
Gamma pass rate

Patient #	$CBCT_{NN}$	$CBCT_{raw}$
1	99.92%	69.18%
2	100%	61.22%
3	100%	65.94%
4	94.18%	64.22%
5	100%	70.32%
6	99.56%	72.15%
7	98.21%	66.55%
8	97.57%	71.14%
9	99.47%	73.12%
10	99.96%	70.59%
Mean	**98.89%**	**68.44%**

$CBCT_{SF}$

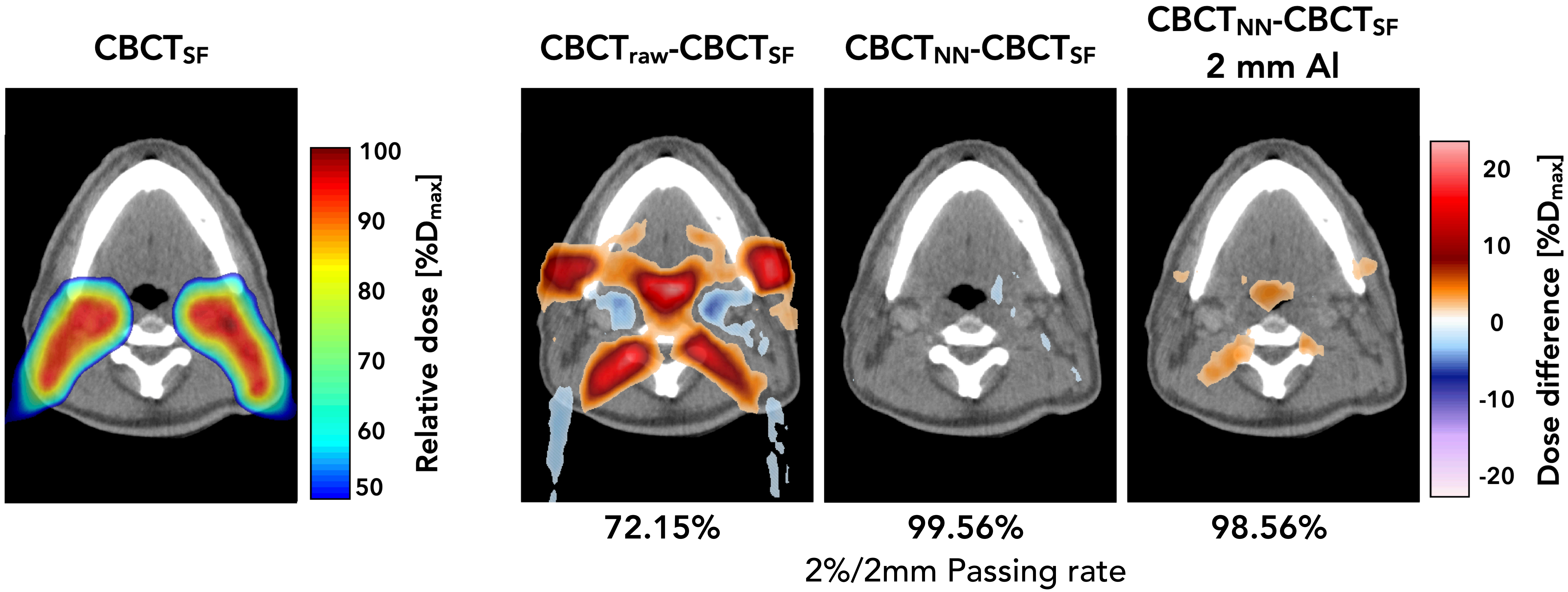


$CBCT_{raw}$-$CBCT_{SF}$ **$CBCT_{NN}$-$CBCT_{SF}$**



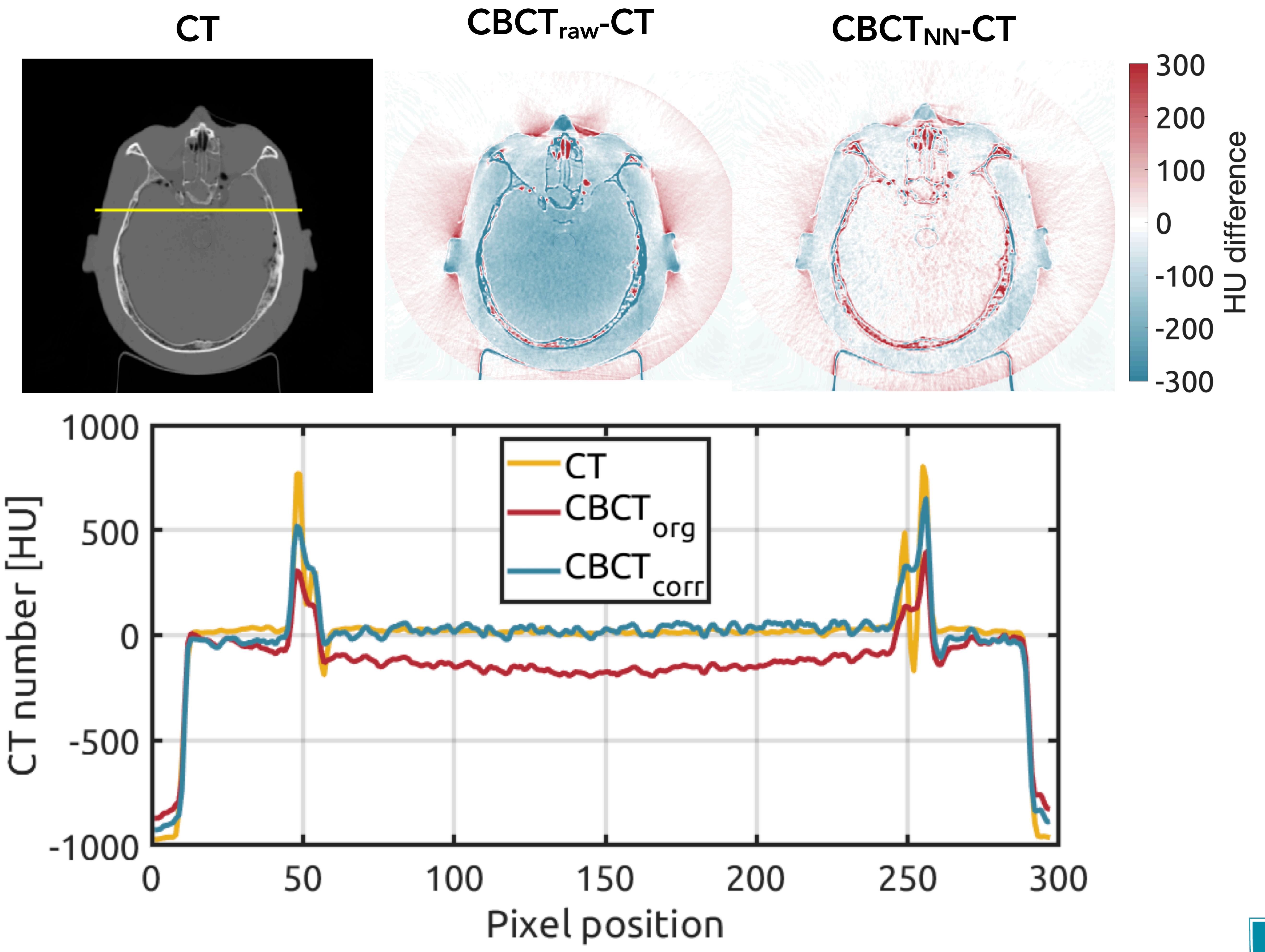
IMPACT OF SPECTRAL ACCURACY

- Similarly as for the HU accuracy, the **spectral model** used for training has **some impact** on the dose calculation accuracy.
- Still a substantial **improvement** over **CBCT$_{raw}$**



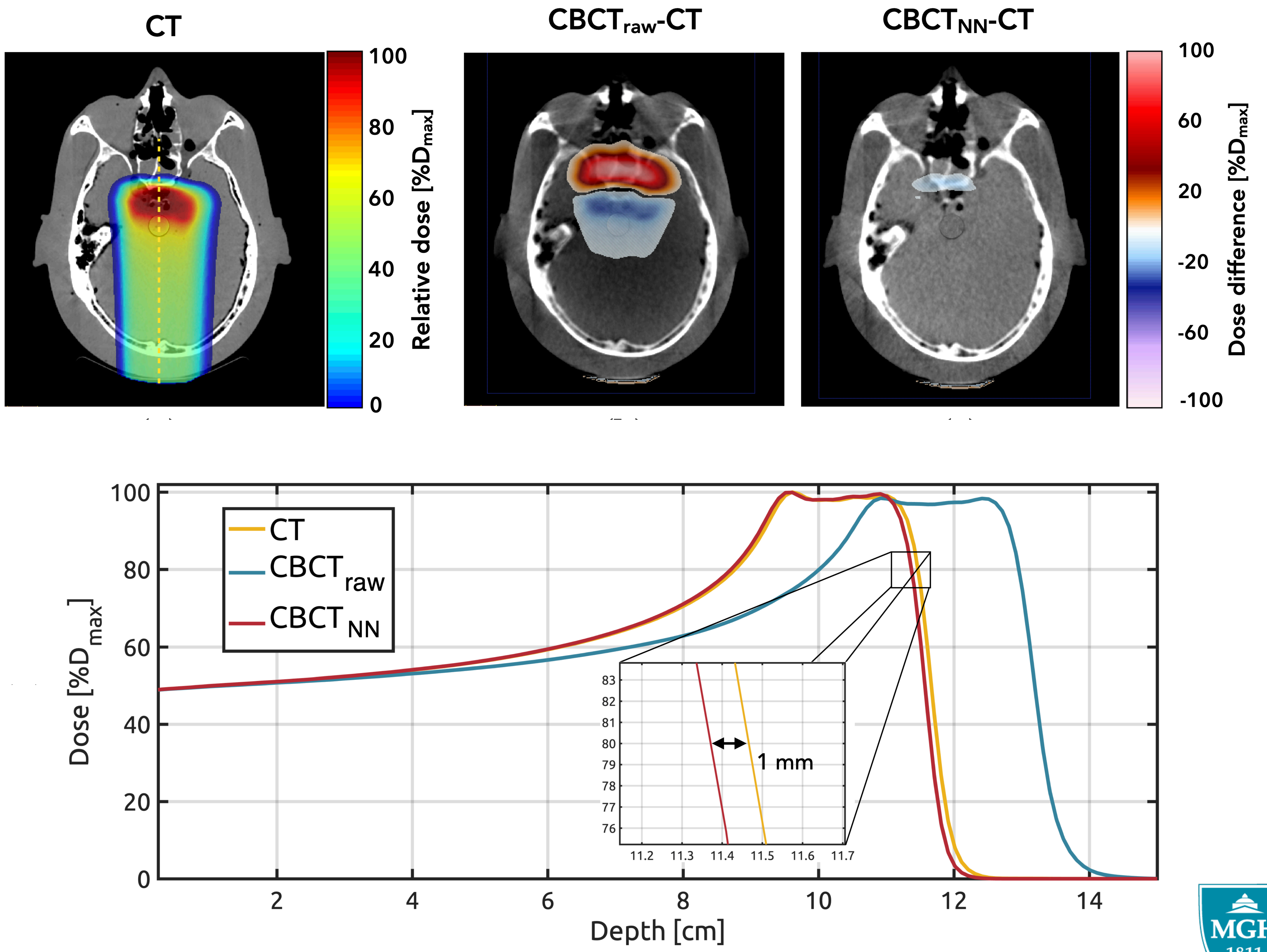
HU ACCURACY - HEAD PHANTOM

- **CBCT projections** of an anthropomorphic phantom containing a **real** human **skull** are acquired on an **Elekta XVI** system.
- Reconstructed CBCT images are compared to a **reference CT** scan of the same phantom.



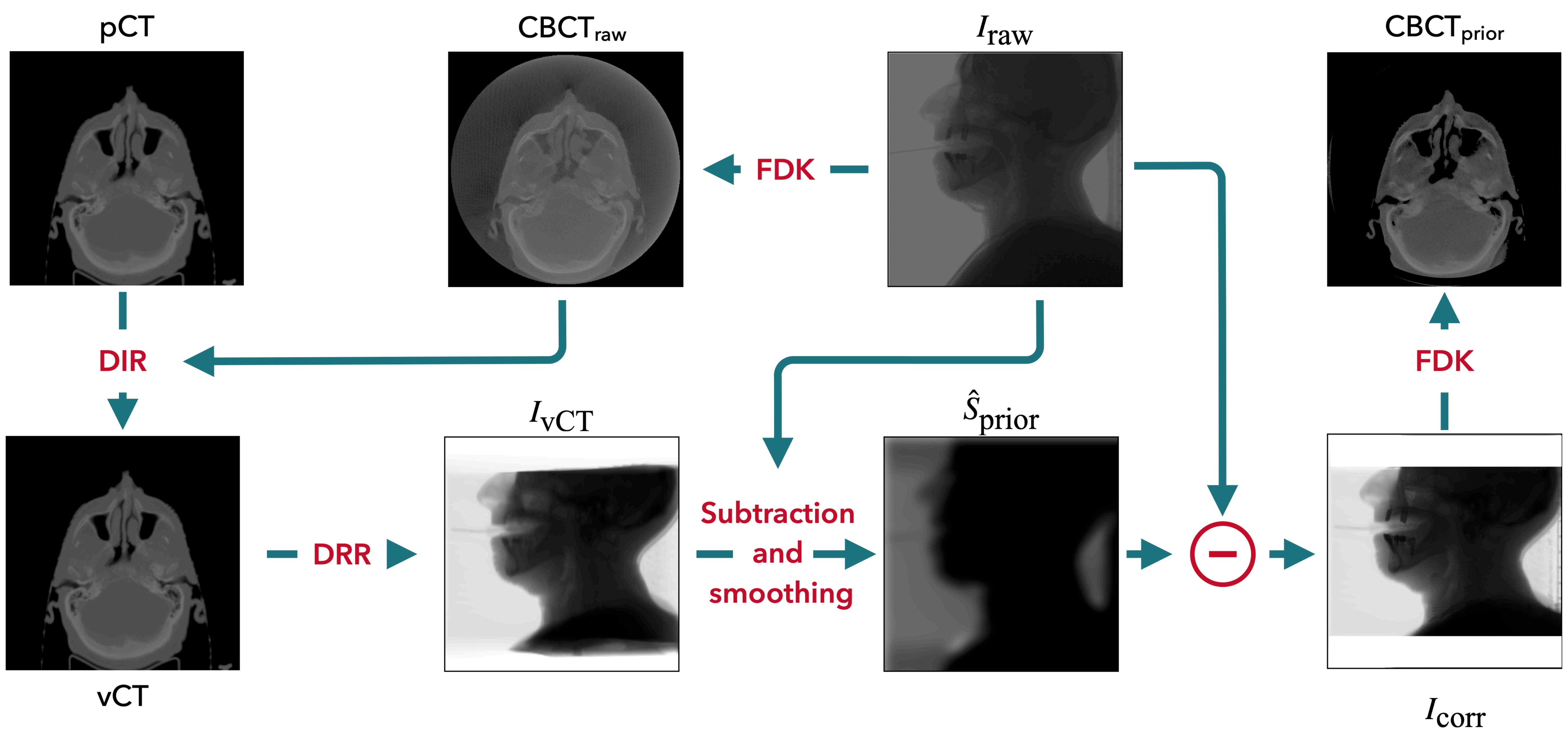
RANGE PREDICTION ACCURACY

- Proton **range accuracy** using the measured **CBCT** images is evaluated in the **head phantom** using the CT image as reference.
- **Millimetric** agreement is obtained between **$CBCT_{NN}$** and the reference **CT** scan.



EVALUATION IN PATIENT DATA

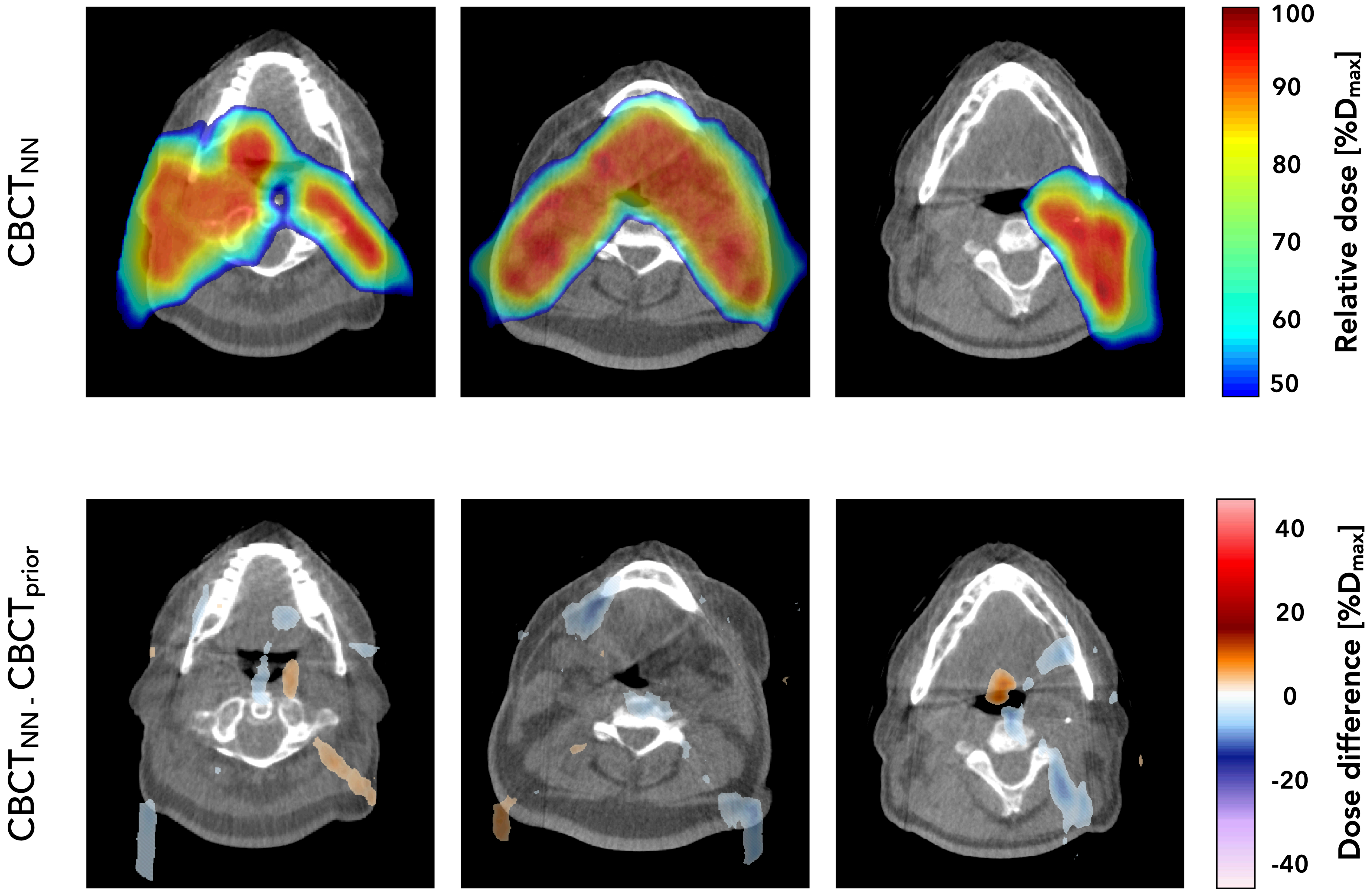
- To evaluate the performance of the method on **real patient data** (no ground truth) the **prior-based** method of Park *et al.* is used as reference
- 3 patients from the test group are used for the comparison between **CBCT$_{NN}$** and **CBCT$_{prior}$**



Park, Y. K., Sharp, G. C., Phillips, J., & Winey, B. A. (2015). Proton dose calculation on scatter-corrected CBCT image: Feasibility study for adaptive proton therapy. *Medical physics*, *42*(8), 4449-4459.

EVALUATION IN PATIENT DATA

- Generally **good agreement** between our MC-based **NN scatter correction** and the **prior-based reference method**
- Mean gamma pass rate of **78.15%** (2%/2mm) and **98.71%** (3%/3mm)



CONCLUSION

- The trained **U-net** is able to provide MC **equivalent** scatter correction in **less** than **5 seconds**,
- Optimal HU **accuracy** is achieved using the **MAPE** cost function and predicting **scatter distributions** instead of scatter free projections,
- The model is **robust** against **moderate** spectral **discrepancies** between training and validation projections,
- **Accurate** proton **range** prediction and IMPT **dose** calculation is achieved on the scatter-corrected CBCT images,
  - The method is **suitable** for head and neck **adaptive proton therapy**.

THANK YOU FOR YOUR ATTENTION!

*For more details, see our recent publication***:**

Physics in Medicine & Biology

IPEM Institute of Physics and Engineering in Medicine

ACCEPTED MANUSCRIPT

Evaluation of CBCT scatter correction using deep convolutional neural networks for head and neck adaptive proton therapy

To cite this article before publication: Arthur Lalonde *et al* 2020 *Phys. Med. Biol.* in press https://doi.org/10.1088/1361-6560/ab9fcb

NSERC CRSNG

Fonds de recherche sur la nature et les technologies Québec

MGH 1811

HARVARD MEDICAL SCHOOL