

Deep Learning-based Iterative Reconstruction for Field of View Extension in Dual-Source Dual-Energy CT

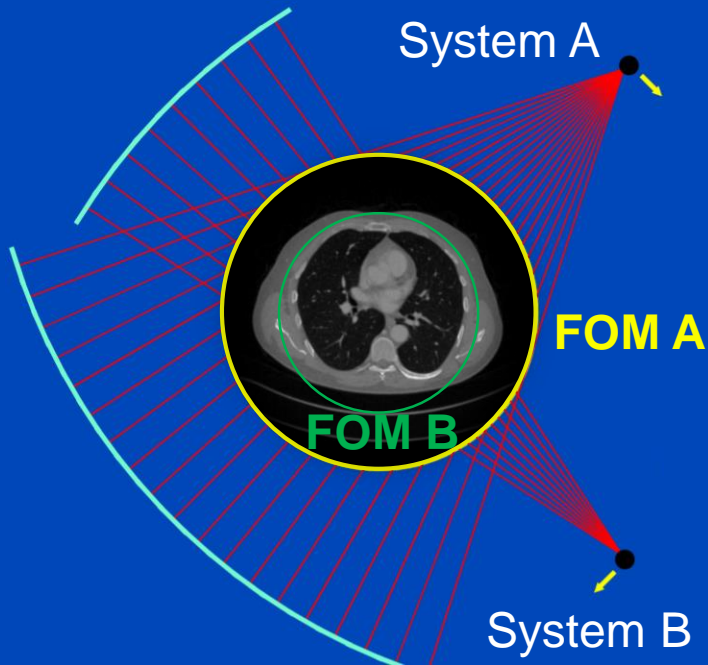
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¹German Cancer Research Center (DKFZ), Heidelberg, Germany

²Ruprecht-Karls-Universität, Heidelberg, Germany

³Siemens Healthineers, Forchheim, Germany

Motivation

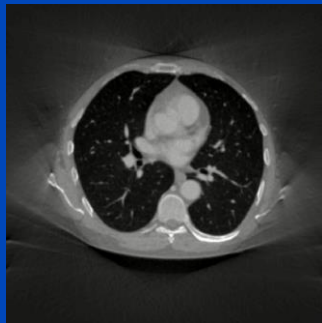


- In dual-source CT, the field of measurement (FOM) of the second source-detector pair is often limited by technical constraints.
- Dual-energy information is only available within the small FOM.
- Deep learning-based iterative reconstruction to recover missing information.

Reconstruction A



Reconstruction B*



*Note: The reconstruction was performed using a custom reconstruction software. The vendor's reconstruction software would clip the reconstruction to the small FOM.

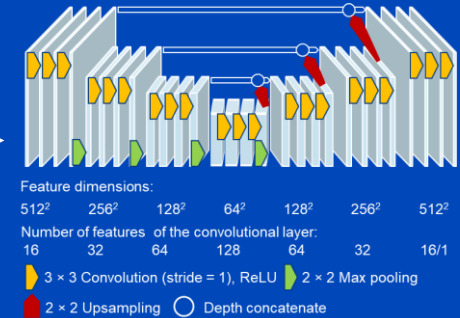
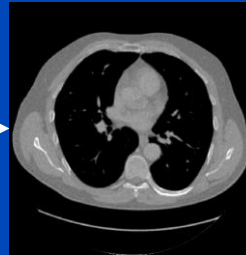
Prior Work

Sinogram, energy A

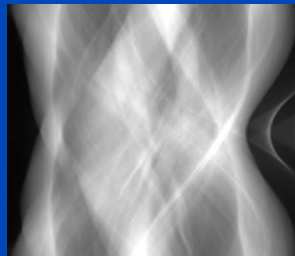


Reconstruction

CT Image, energy A

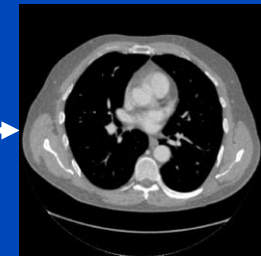


Sinogram, energy B



(Training)

CT Image, energy B



- [1] D. Lee et al., “Development of a deep neural network for generating synthetic dual-energy chest x-ray images with single x-ray exposure”, *Phys. Med. Biol.*, 2019.
- [2] Y. Liao et al., “Pseudo dual energy CT imaging using deep learning-based framework: basic material estimation”, *SPIE*, 2018.
- [3] W. Zhao et al., “A deep learning approach for dual-energy CT imaging using a single-energy CT data”, *Fully 3D*, 2019.
- [4] C. K. Liu, C. C. Liu, C. H. Yang, H. M. Huang, “Generation of brain dual-energy CT from single-energy CT using deep learning”, *J. Digit. Imaging*, 2021.
- [5] T. Lyu et al., “Estimating dual-energy CT imaging from single-energy CT data with material decomposition convolutional neural network”, *Med. Img. Anal.*, 2021.
- [6] Y. Li et al., “Deep-En-Chroma: mining the spectral fingerprints in single-kV CT acquisitions using energy integration detectors”, *SPIE*, 2022.
- [7] D. P. Clark et al., “Deep learning based spectral extrapolation for dual-source, dual-energy x-ray computed tomography”, *Med. Phys.*, 2020.
- [9] L. Yao et al., “Leveraging deep generative model for direct energy-resolving CT imaging via existing energy-integrating CT images”, *SPIE*, 2020.

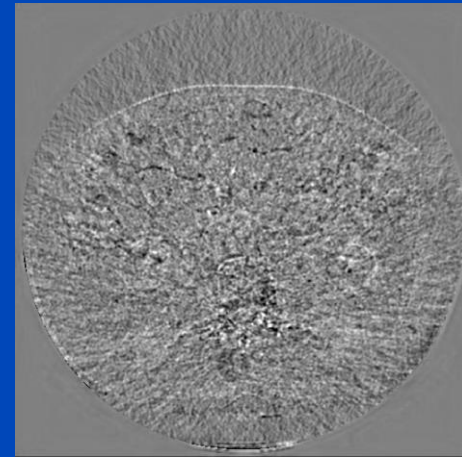
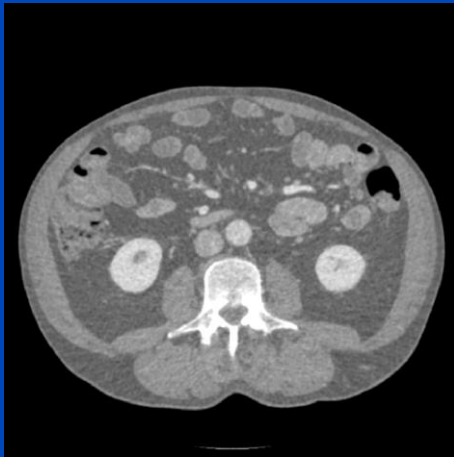
Single-Energy Mappings

Input to network

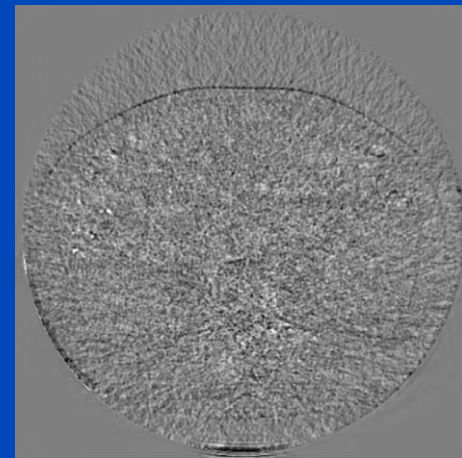
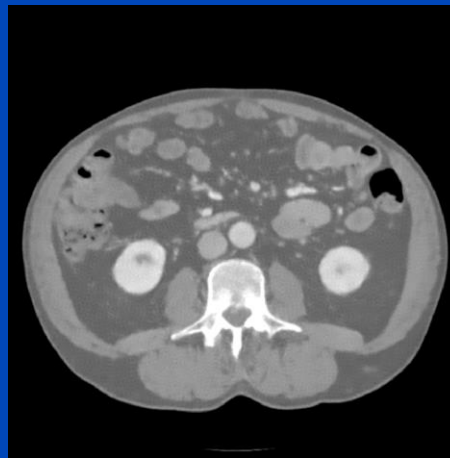
Prediction

Error w.r.t. ground truth

70 kV to 150 kV
mapping



150 kV to 70 kV
mapping



$C = 0$ HU, $W = 1000$ HU

$C = 0$ HU, $W = 300$ HU

Single-Energy Mappings

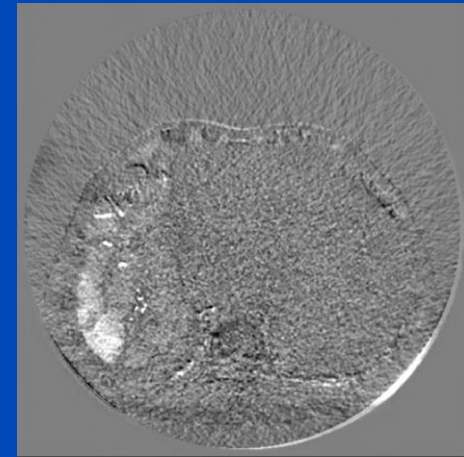
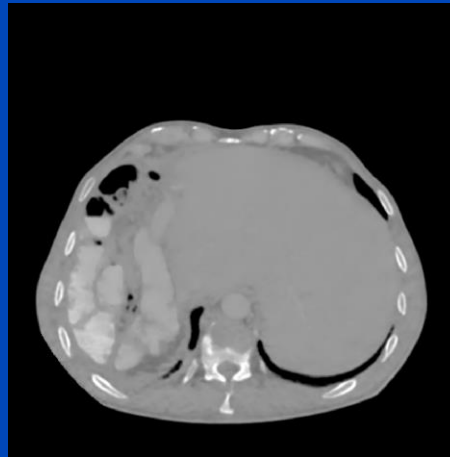
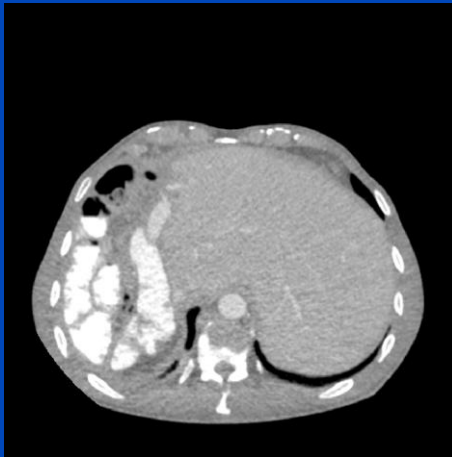
Out-of-distribution samples

Input to network

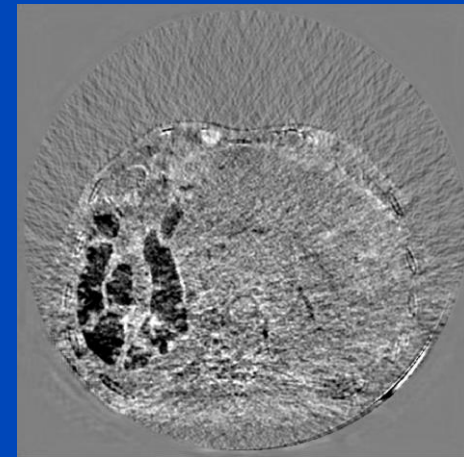
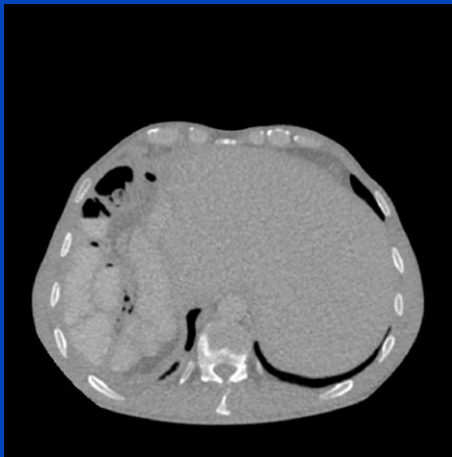
Prediction

Error w.r.t. ground truth

70 kV to 150 kV
mapping



150 kV to 70 kV
mapping

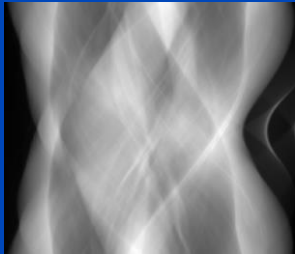


$C = 0$ HU, $W = 1000$ HU

$C = 0$ HU, $W = 300$ HU

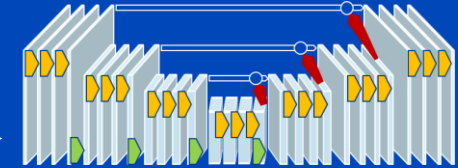
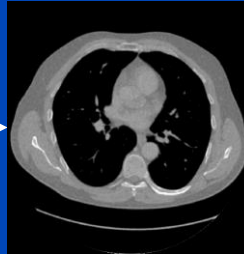
Single-Energy Mapping

Sinogram, energy A



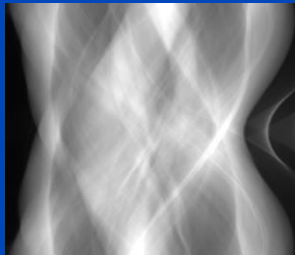
Reconstruction

CT Image, energy A



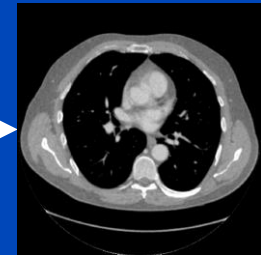
Feature dimensions:
512² 256² 128² 64² 128² 256² 512²
Number of features of the convolutional layer:
16 32 64 128 64 32 16/1
3 × 3 Convolution (stride = 1), ReLU 2 × 2 Max pooling
2 × 2 Upsampling ○ Depth concatenate

Sinogram, energy B



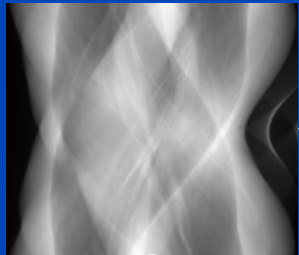
(Training)

CT Image, energy B



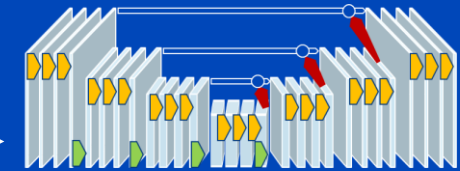
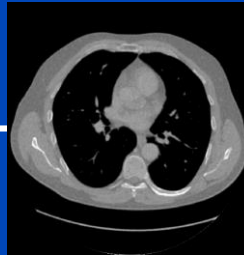
Proposed Approach

Sinogram of current estimate



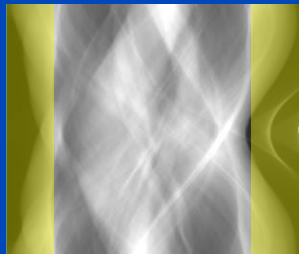
Forward projection

Current estimate

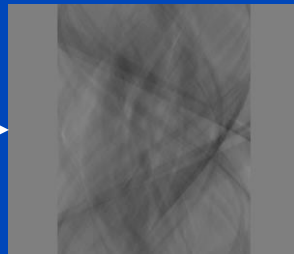


Feature dimensions:
512² 256² 128² 64² 128² 256² 512²
Number of features of the convolutional layer:
16 32 64 128 64 32 16/1
3 × 3 Convolution (stride = 1), ReLU 2 × 2 Max pooling
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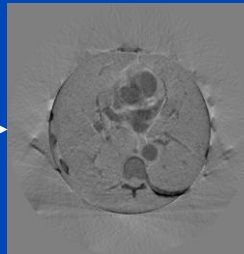
Sinogram, energy B



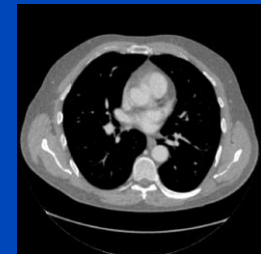
Raw data fidelity



Update image



CT Image, energy B

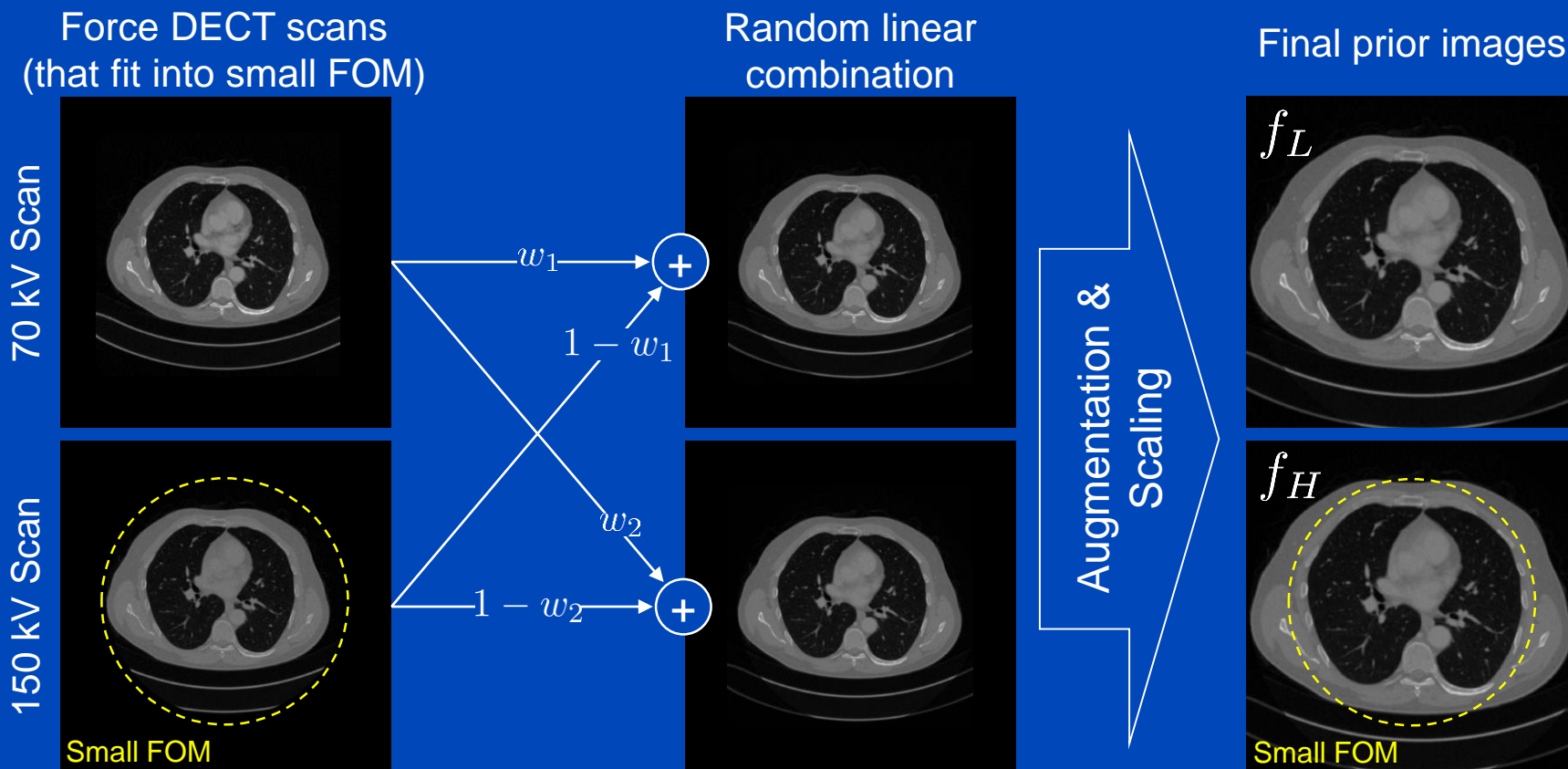


(Training)

Make use of limited angle information outside small FOM to learn a more reliable mapping.

Training Data Generation

Prior images



→ Forward projection of prior images to generate synthetic raw data.

Results

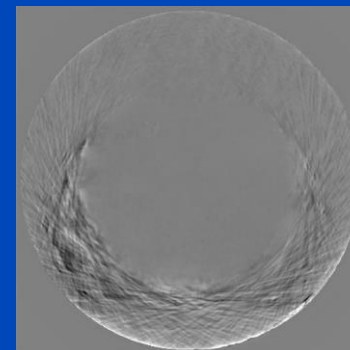
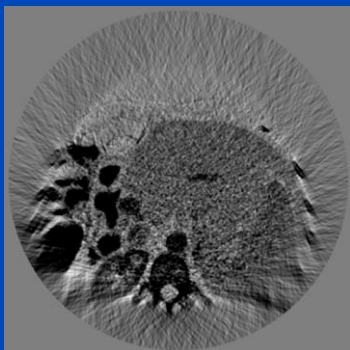
Simulated data

Input, 150 kV

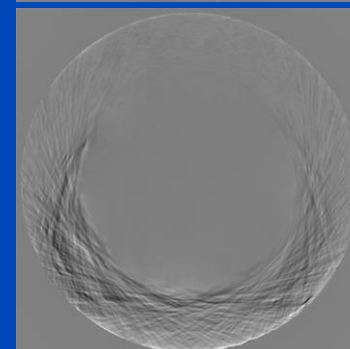
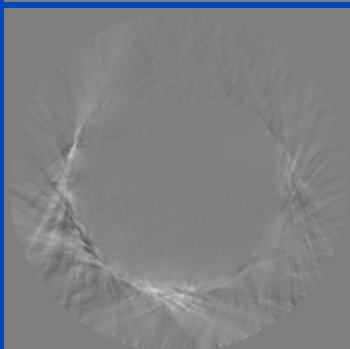
Ground truth, 70 kV

Prediction - GT

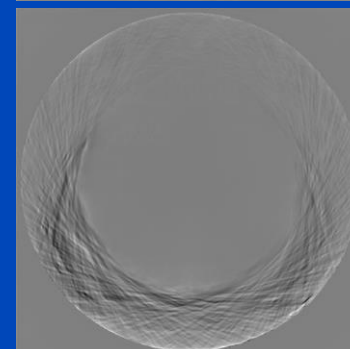
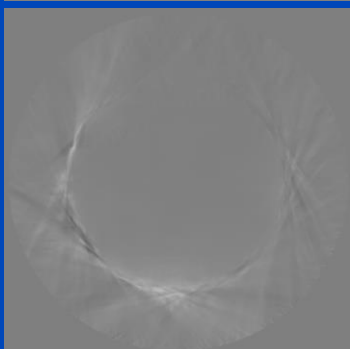
1st iteration



2nd iteration



3rd iteration



C = 0 HU, W = 1000 HU

C = 0 HU, W = 400 HU

C = 0 HU, W = 1000 HU

C = 0 HU, W = 300 HU

Results

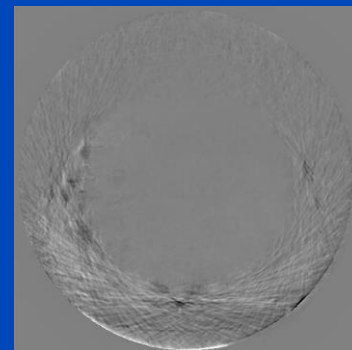
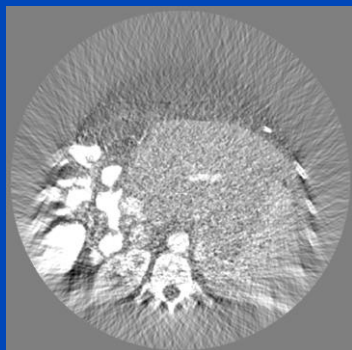
Simulated data

Input, 70 kV

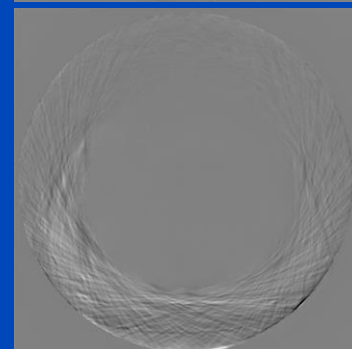
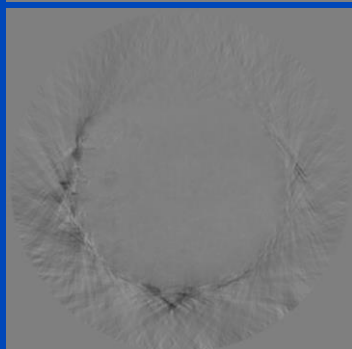
Ground truth, 150 kV

Prediction - GT

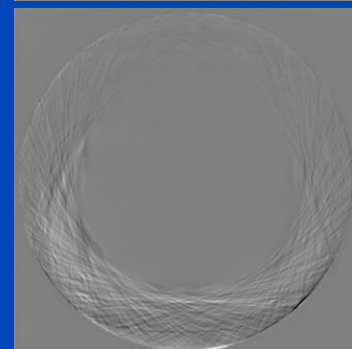
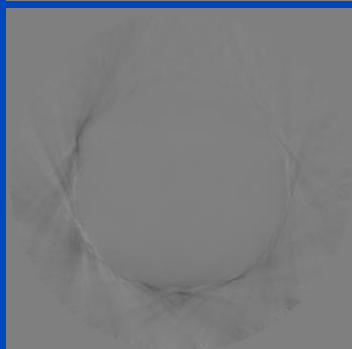
1st iteration



2nd iteration



3rd iteration



C = 0 HU, W = 1000 HU

C = 0 HU, W = 400 HU

C = 0 HU, W = 1000 HU

C = 0 HU, W = 300 HU

Results

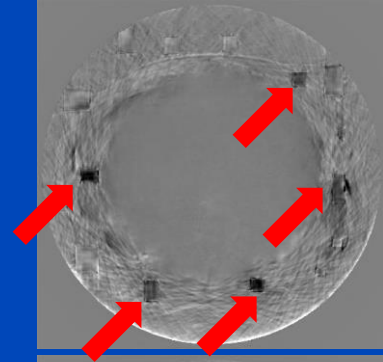
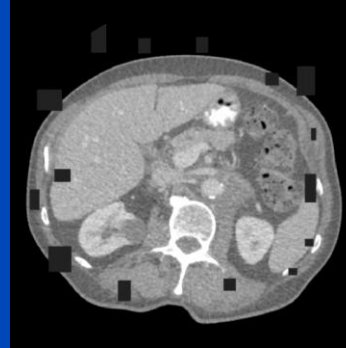
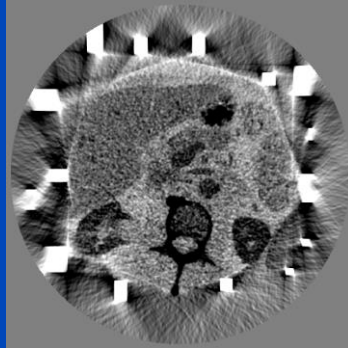
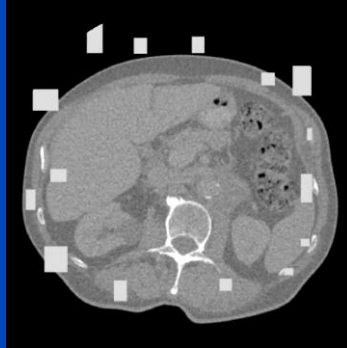
Simulated data

Input, 150 kV

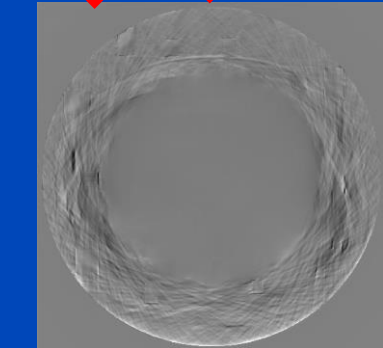
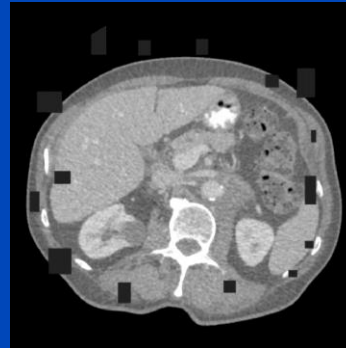
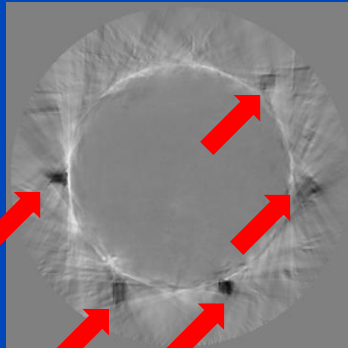
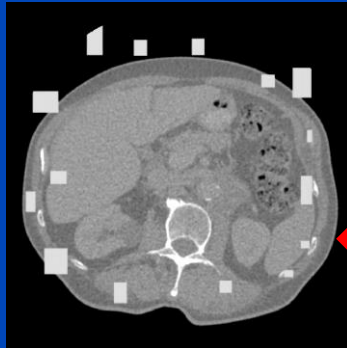
Ground truth, 70 kV

Prediction - GT

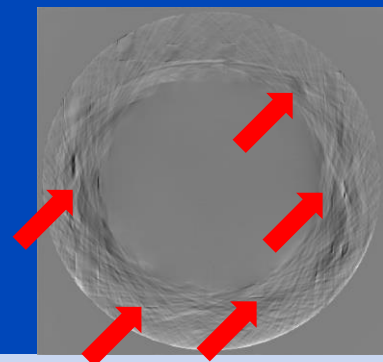
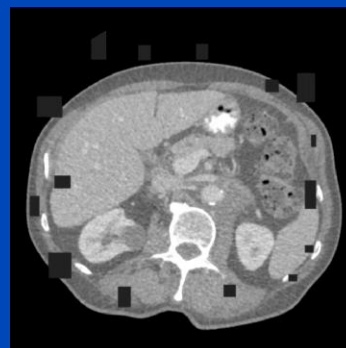
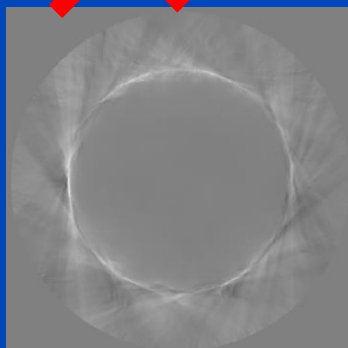
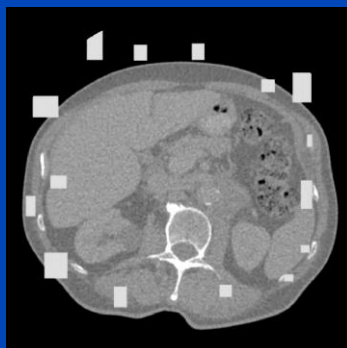
1st iteration



2nd iteration



3rd iteration



C = 0 HU, W = 1000 HU

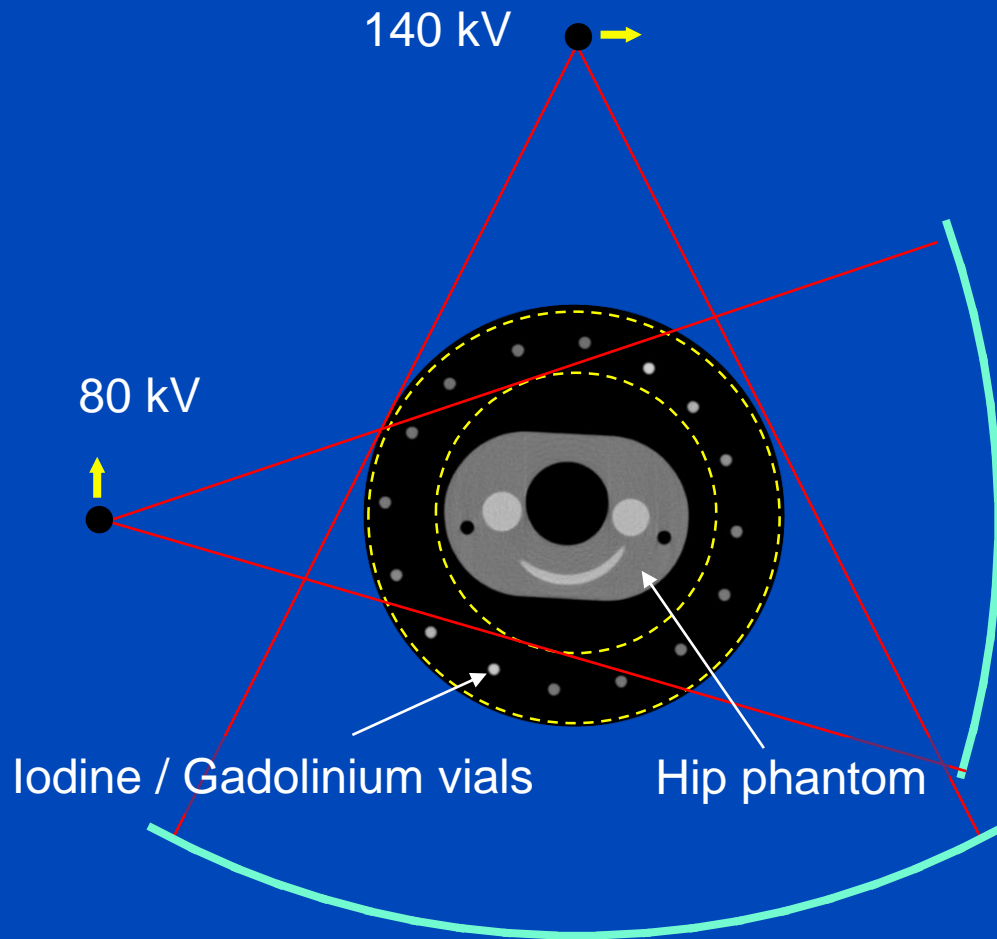
C = 0 HU, W = 400 HU

C = 0 HU, W = 1000 HU

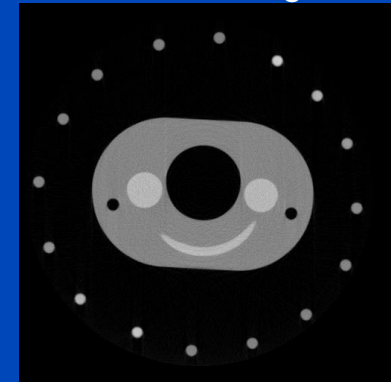
C = 0 HU, W = 300 HU

Measurements

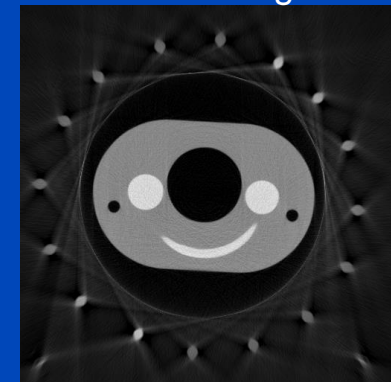
Siemens SOMATOM Definition Flash



140 kV Image

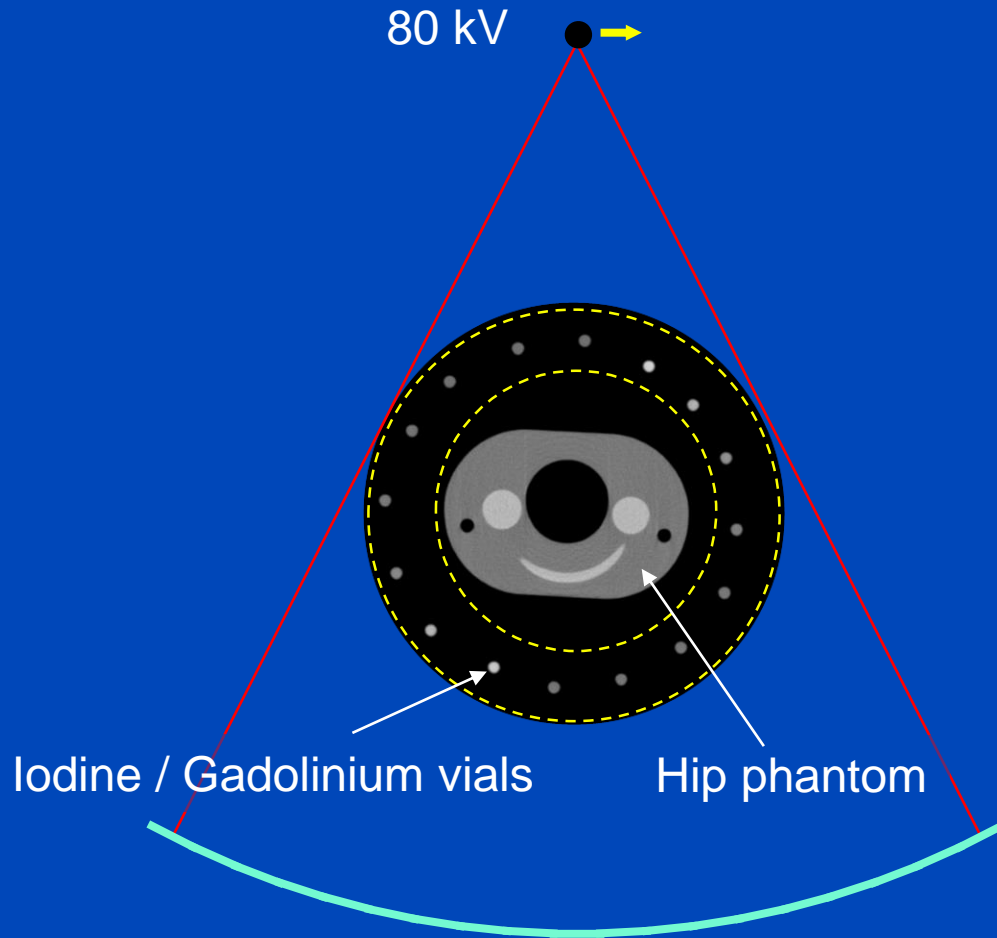


80 kV Image



Measurements

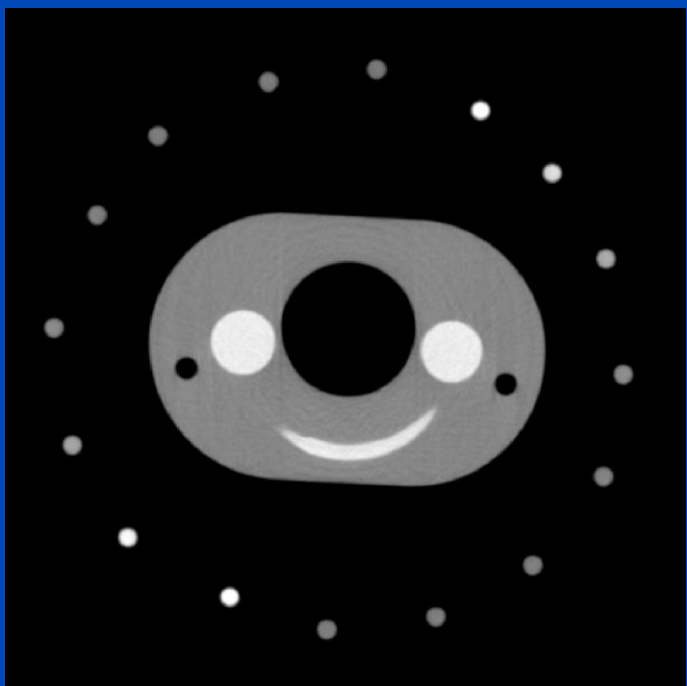
Siemens SOMATOM Definition Flash: Reference measurement



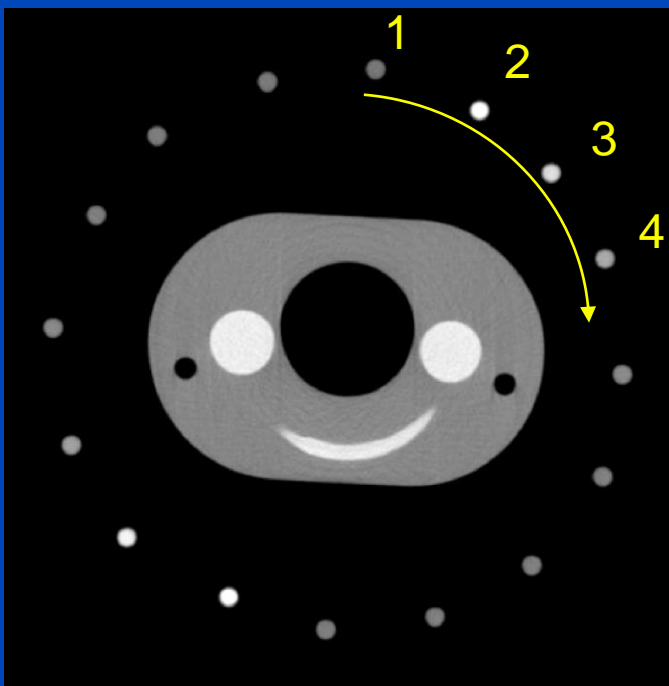
Results

Siemens SOMATOM Definition Flash

80 kV reference



Prediction



$C = 0$ HU, $W = 1400$ HU

ROI	CT #	Error
1	-43 HU	-9 HU
2	853 HU	3 HU
3	559 HU	10 HU
4	252 HU	-2 HU
5	72 HU	-12 HU
6	10 HU	-12 HU
7	-2 HU	-3 HU
8	12 HU	13 HU
9	-5 HU	7 HU
10	977 HU	11 HU
11	684 HU	20 HU
12	198 HU	-15 HU
13	61 HU	-4 HU
14	4 HU	-3 HU
15	-3 HU	6 HU
16	-27 HU	-1 HU

Conclusions

- Proposed approach is able to provide accurate dual-energy information for the entire FOM.
- The current training strategy allows to have one network for any tube voltage combination.
- Iterative application of the proposed approach may improve the quality of the prediction, especially for out-of-distribution samples.

Thank You!

This presentation will soon be available at www.dkfz.de/ct

Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (www.dkfz.de), or directly through Prof. Dr. Marc Kachelrieß (marc.kachelriess@dkfz.de).

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