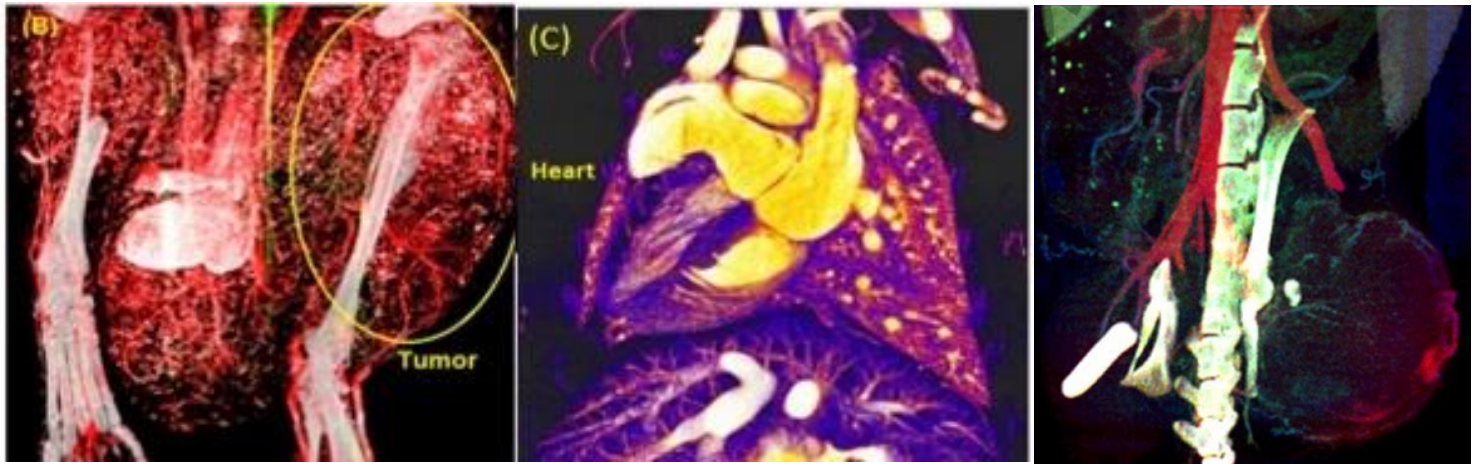


Deep Learning Approaches in Spectral CT

C.T. Badea, PhD

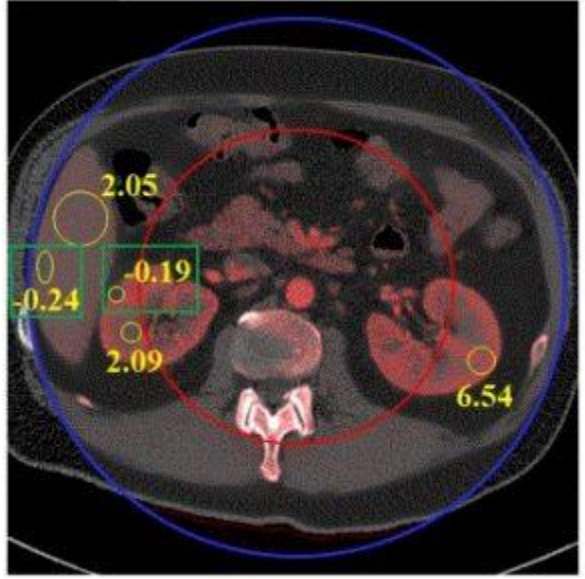
Duke University

Quantitative Imaging and Analysis Lab

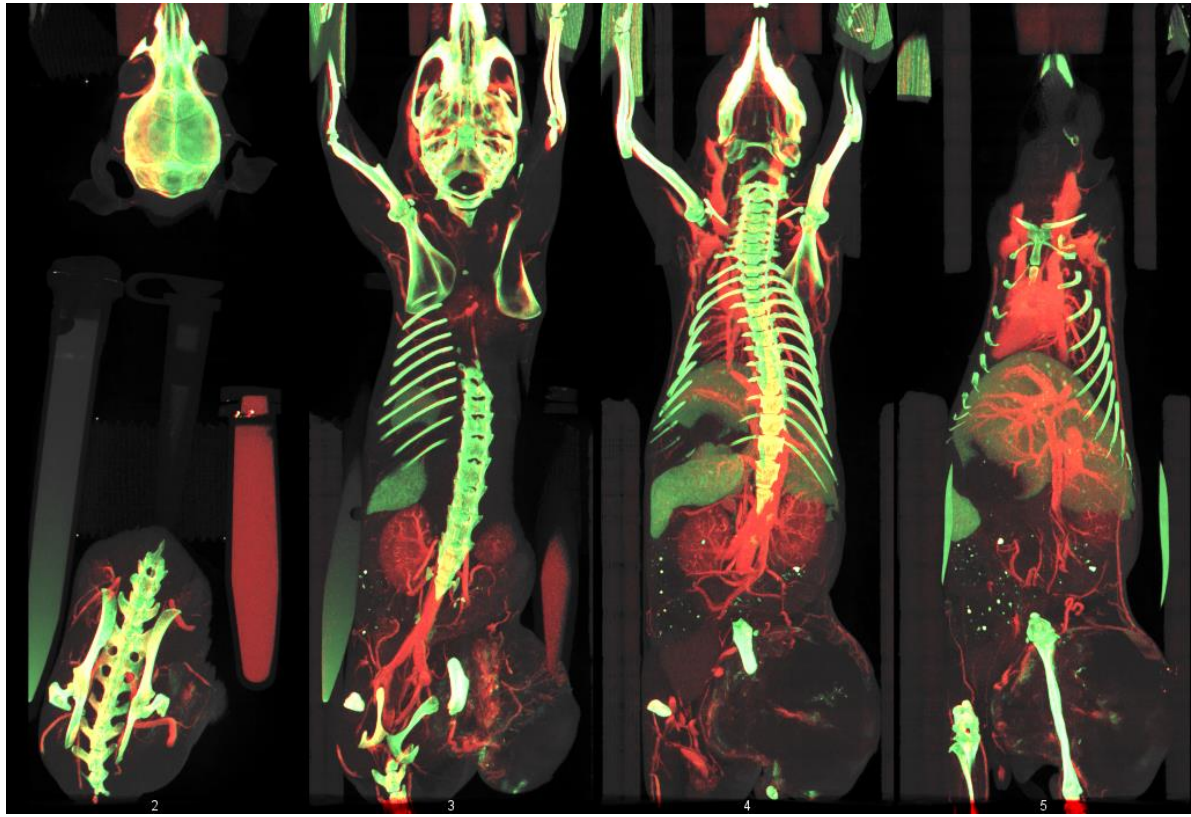
Cristian.Badea@duke.edu

11/10/2020

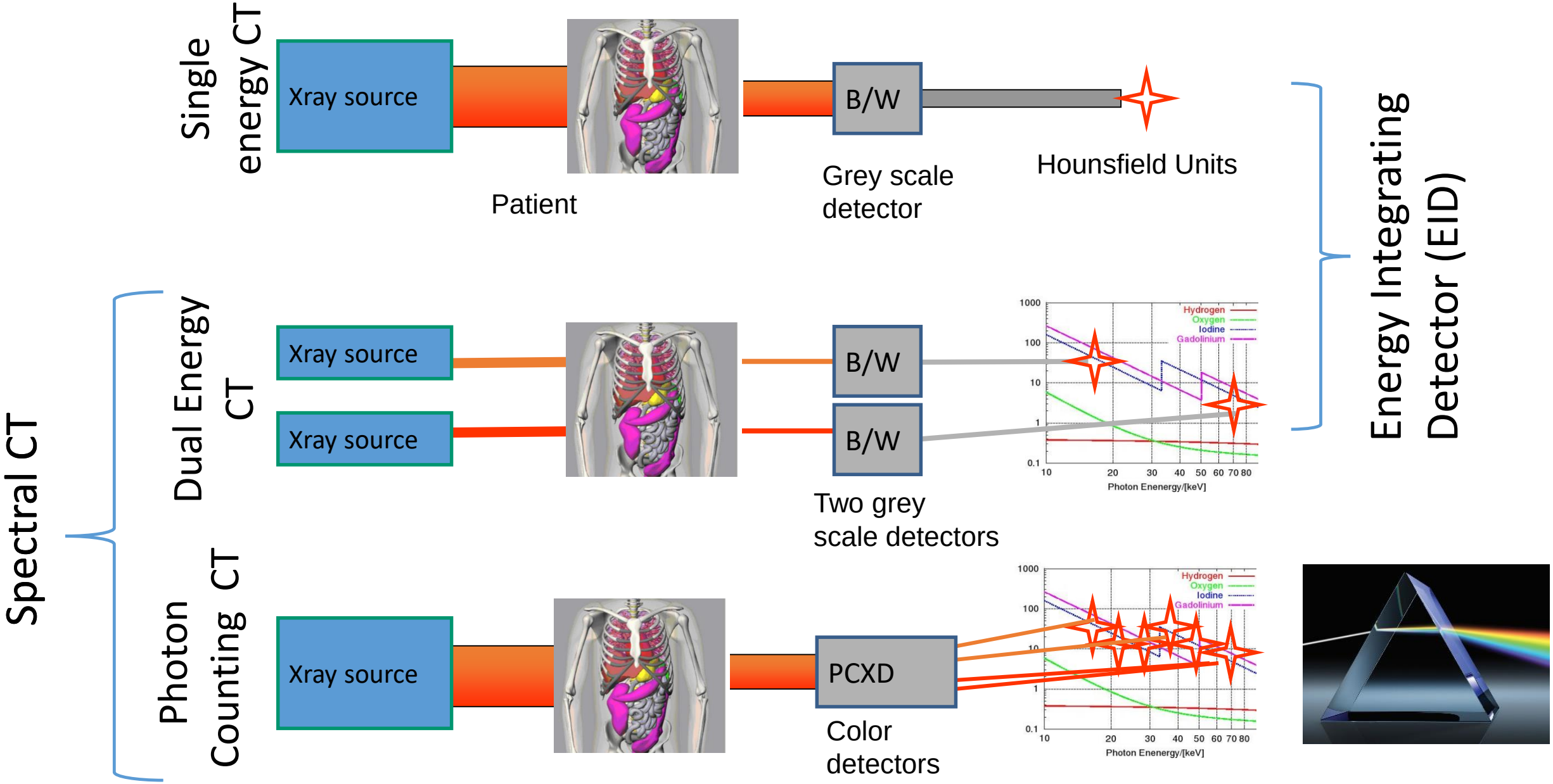
Contents



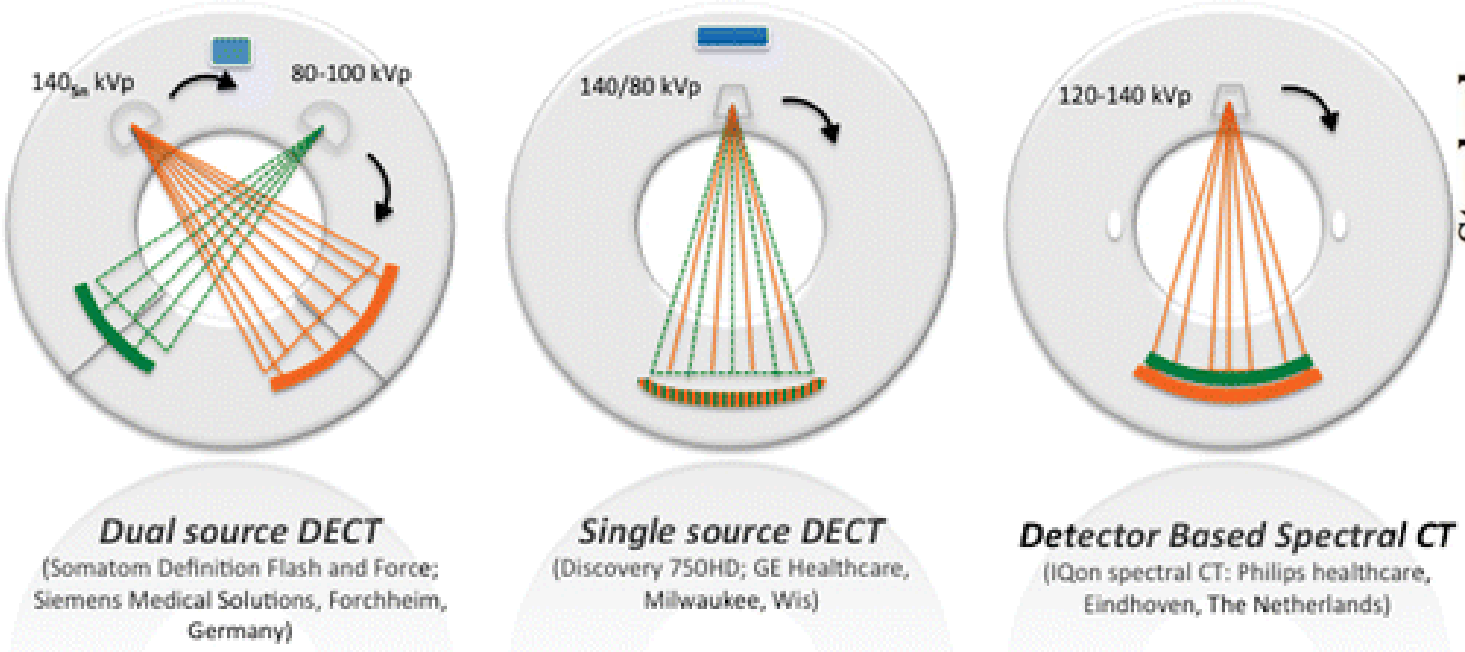
- Spectral CT: Introduction
- Duke Preclinical Photon Counting CT Prototypes
- Challenges solved via DL
  - Ring Artifacts Corrections
  - Increased resolution
  - Noise Reduction in 5D CT
  - Spectral Extrapolation for Dual Source Clinical CT

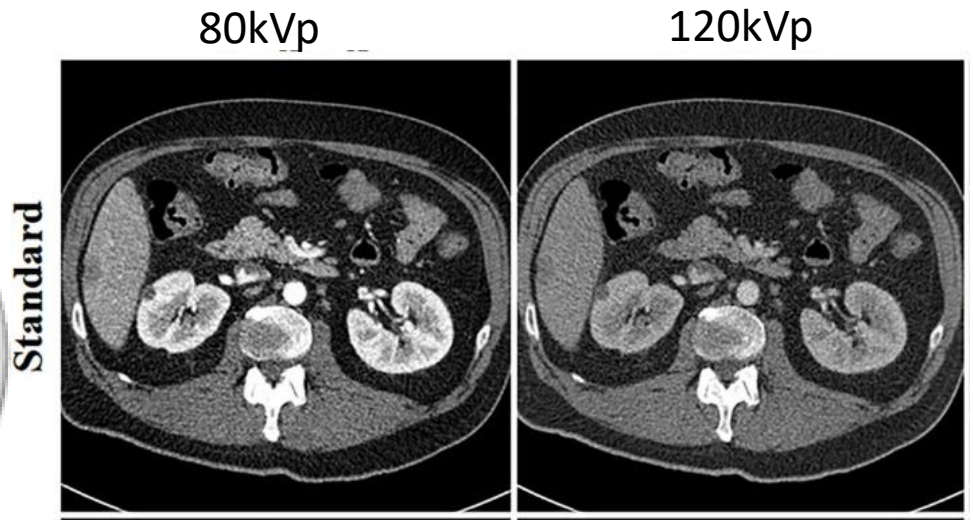


Single-, dual-, and photon counting CT

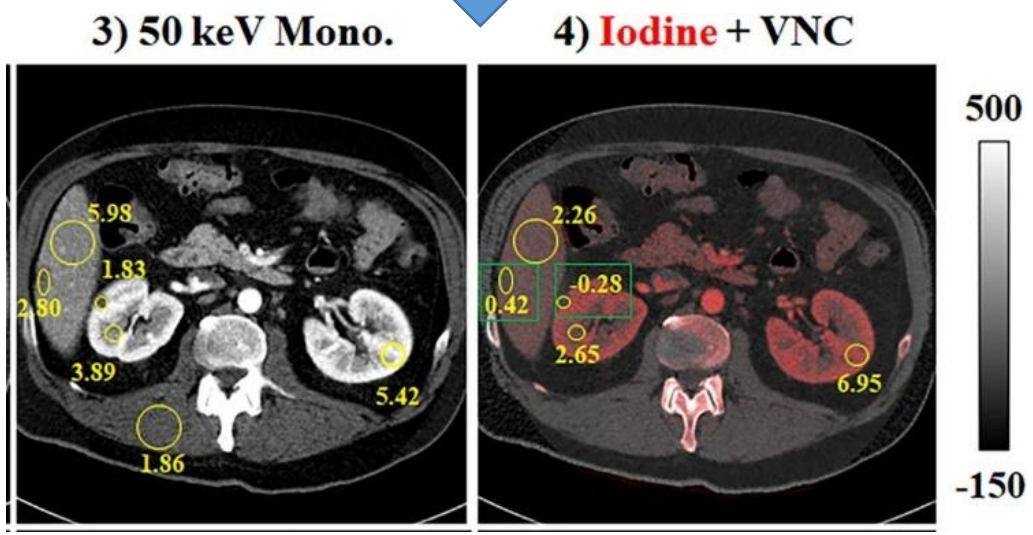


Dual Energy CT based on Energy Integrating Detectors (EID)



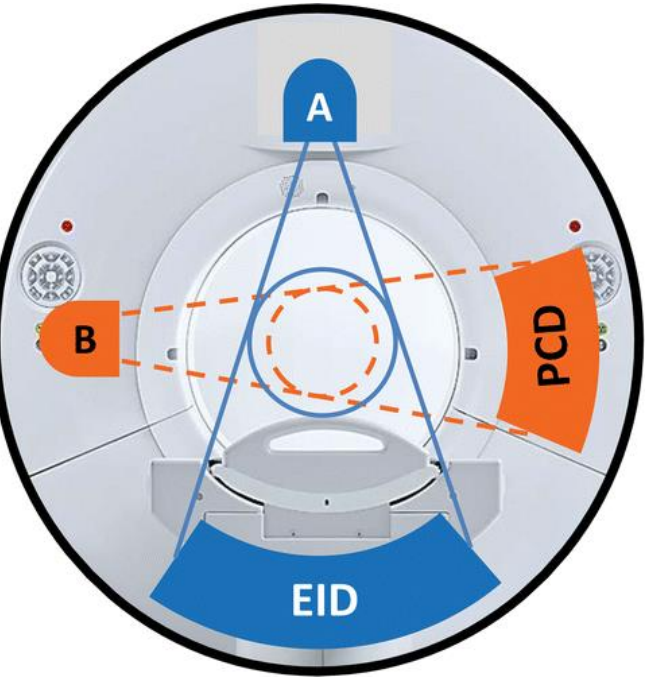


Spectral Decomposition

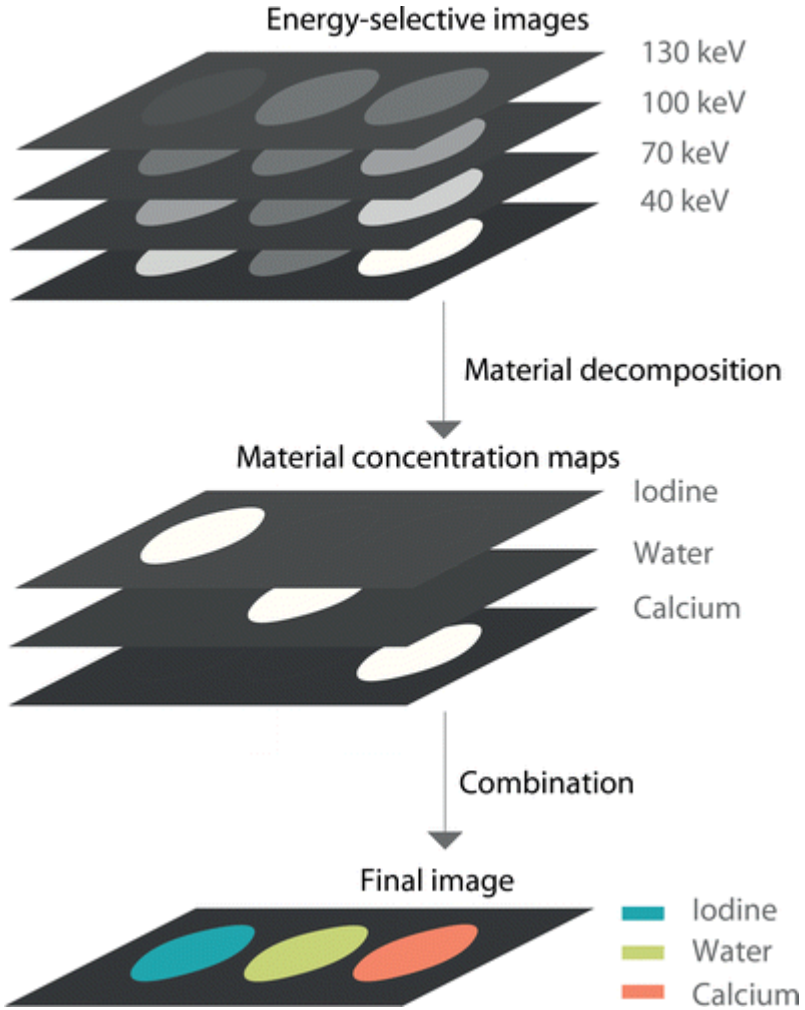


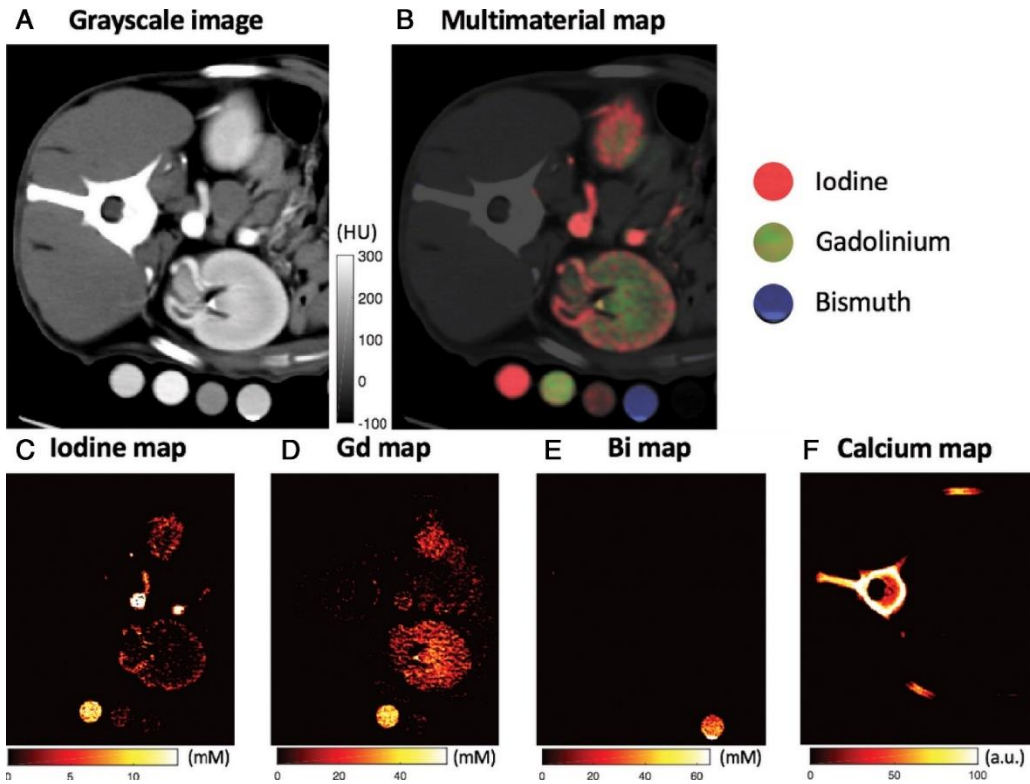
Patino, M. et al, *Radiographics,* Vol. 36, No. 4. 2016

Photon Counting CT



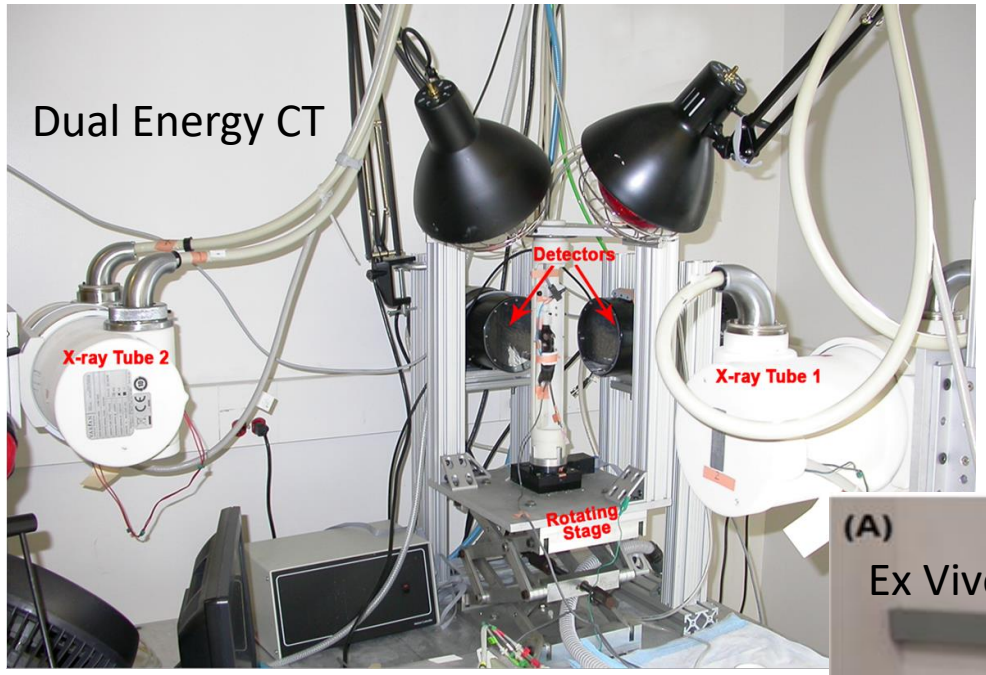
Siemens Hybrid System



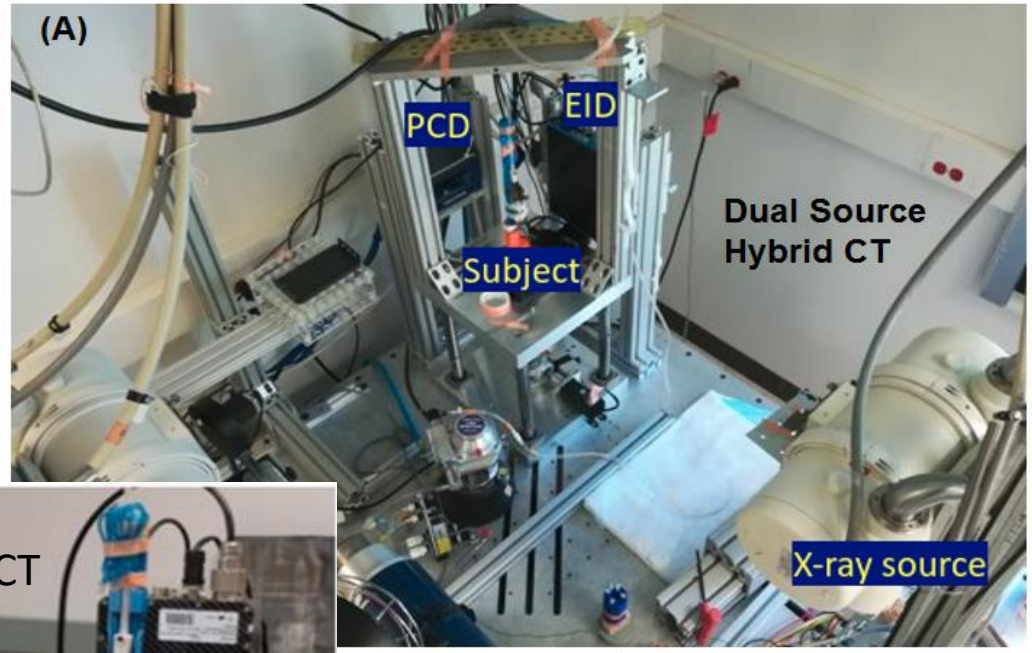


Willemink M, et al, Radiology, Vol. 289, No. 2, 2018

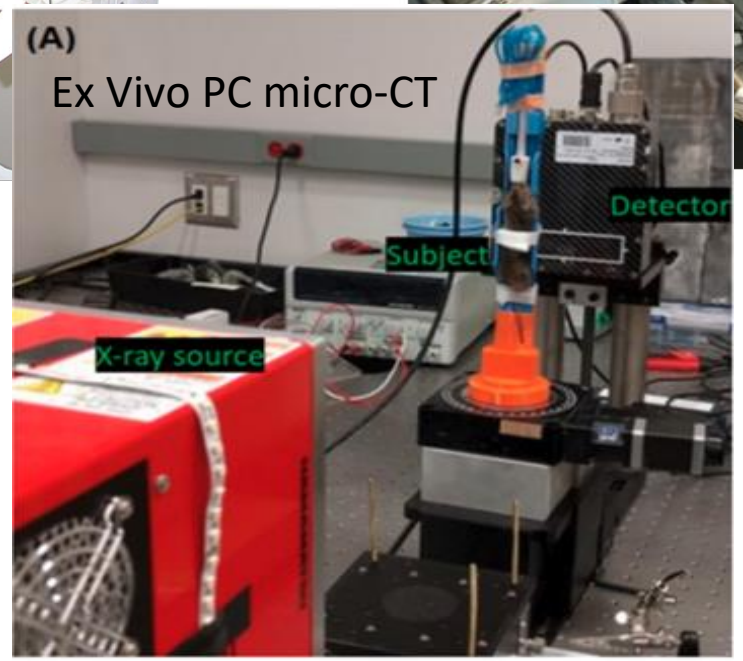
Preclinical Spectral CT at Duke



Badea CT et al, Proc Spie Int Soc Opt Eng, 6913:691342, 2008



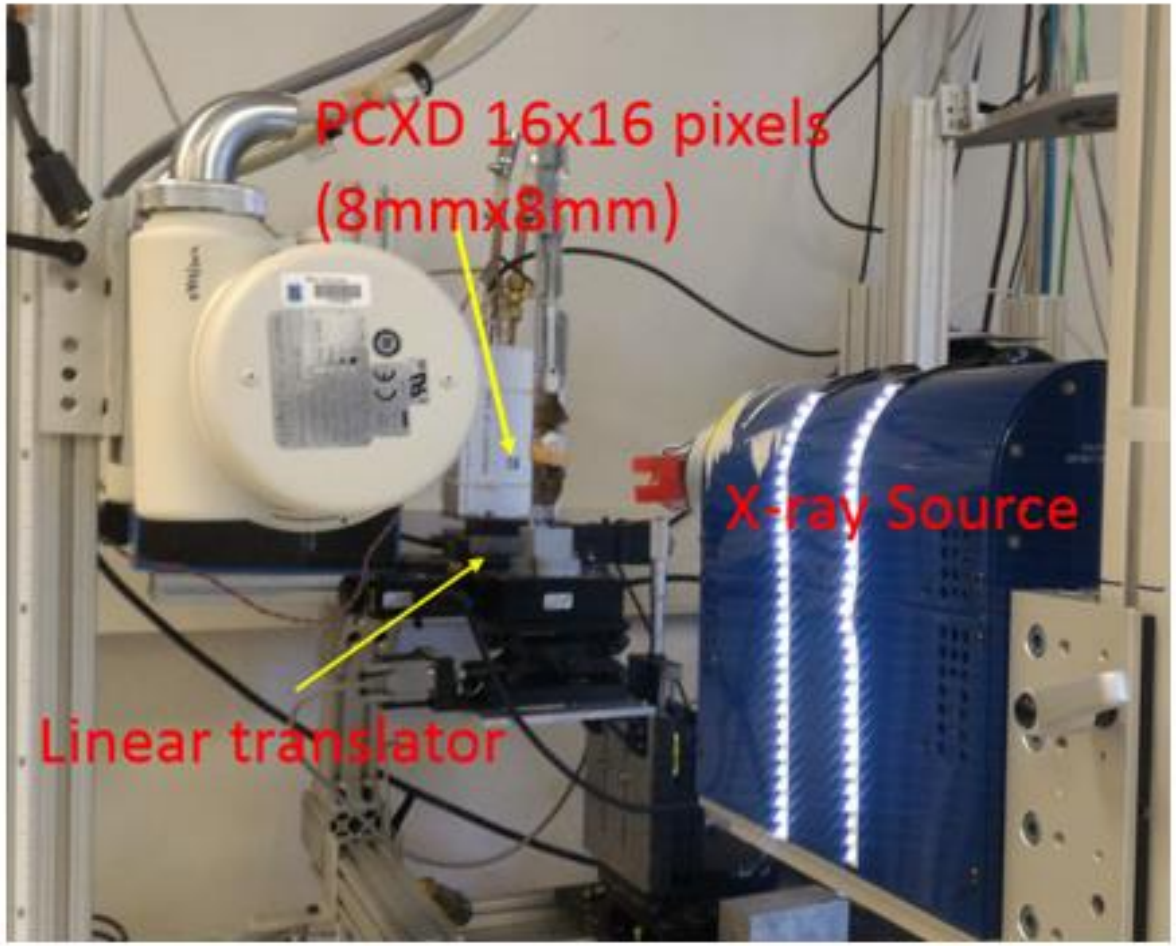
Holbrook, M et al, *Phys Med Biol* 65, no. 20, 205012, 2020



https://sites.duke.edu/qial/spectral-ct/

Holbrook, M, *Spie*, Vol. 11312, 2020

Our First PCD Micro-CT Prototype



- **A translate-rotate geometry**
- PCD (DxRay) is on a horizontal linear translator controlled via LabVIEW
- X-ray source PXS10 MicroFocus
- The four detector thresholds were set to 25, 33, 45, and 80 keV

Holbrook, M, et al, *Med Imaging* 6, no. 1 (2019): 011004

Pre-Reconstruction Processing

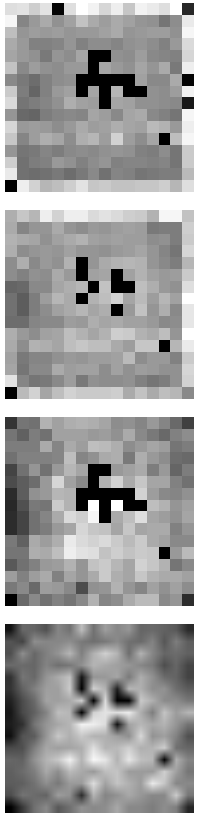
Threshold raw images

1

2

3

4

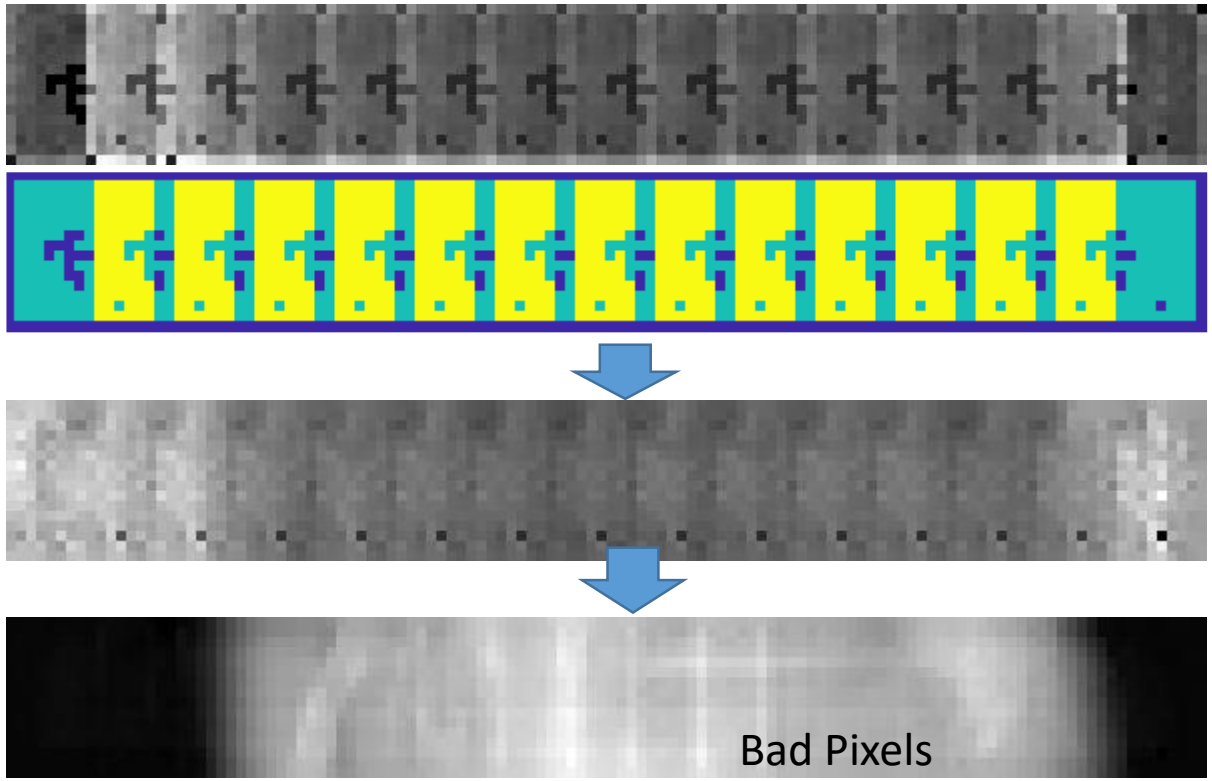


Raw projection

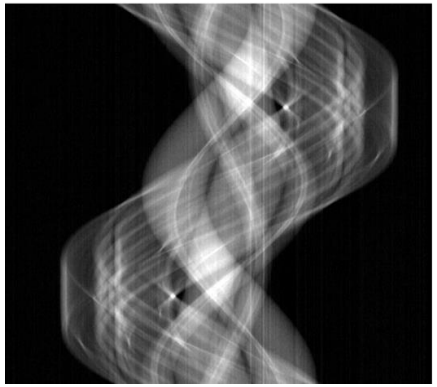
Bad pixel map

Interpolated projection

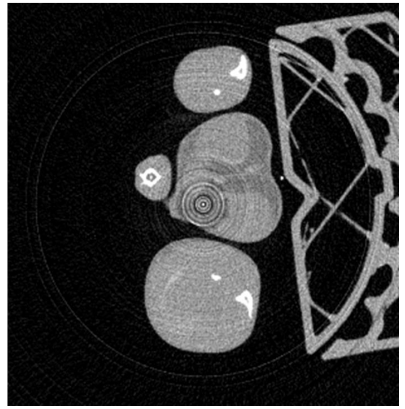
Normalized and log corrected



Acquired Sinogram



Tomographic image



Ring artifacts

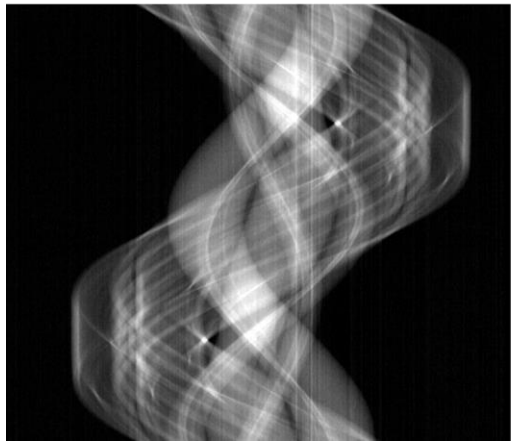
Holbrook, M, et al, *Med Imaging* 6, no. 1 ,2019): 011004

DL Case Study 1:
Ring Artifacts Corrections for Micro-CT

M. Holbrook

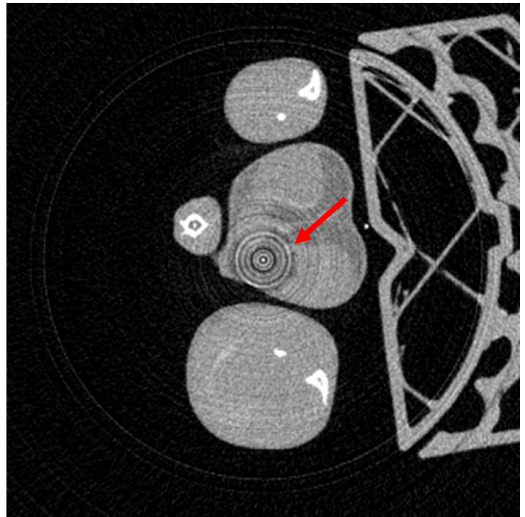
D. Clark

Acquired Sinogram

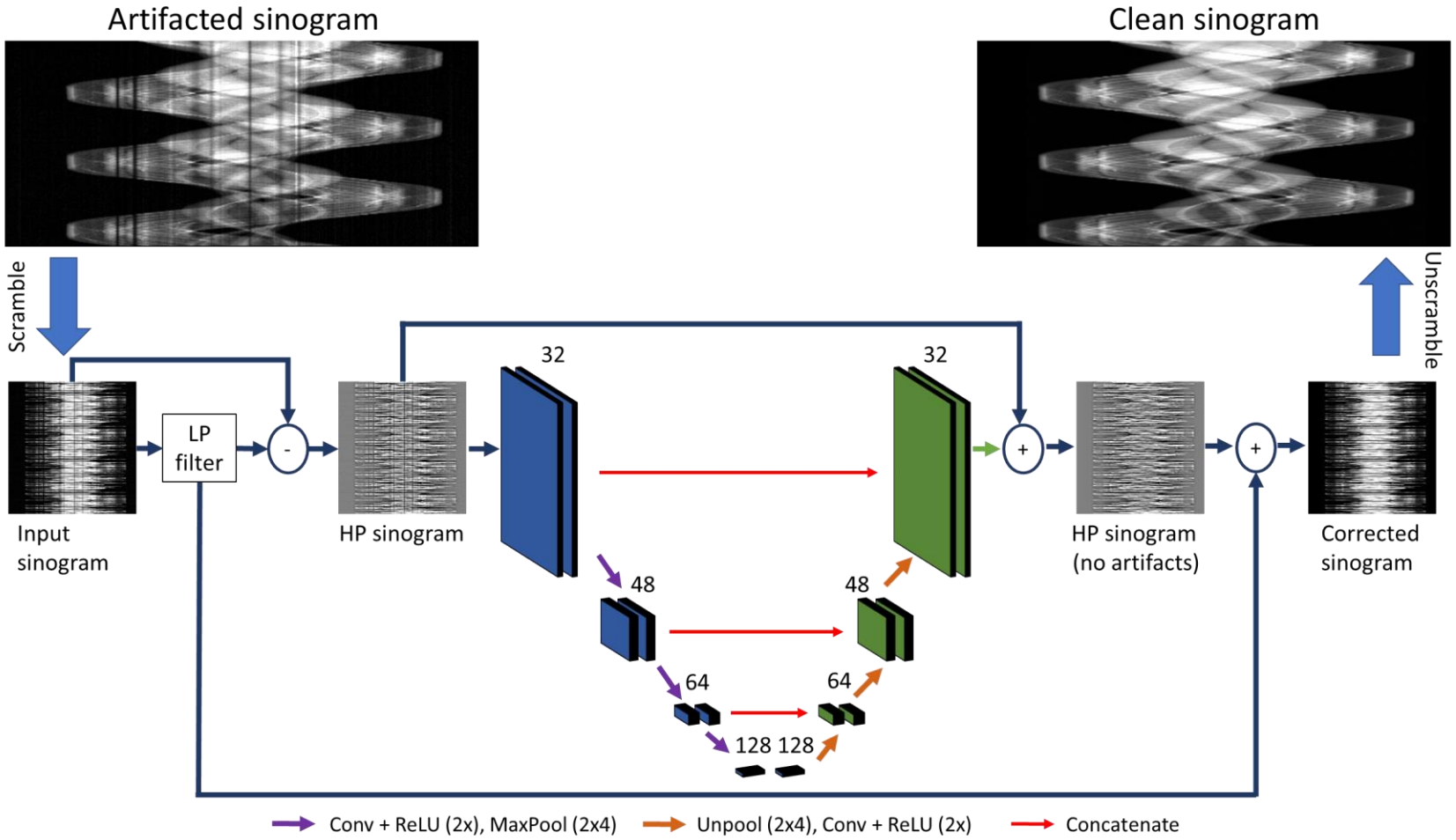


Reconstruction

Tomographic image

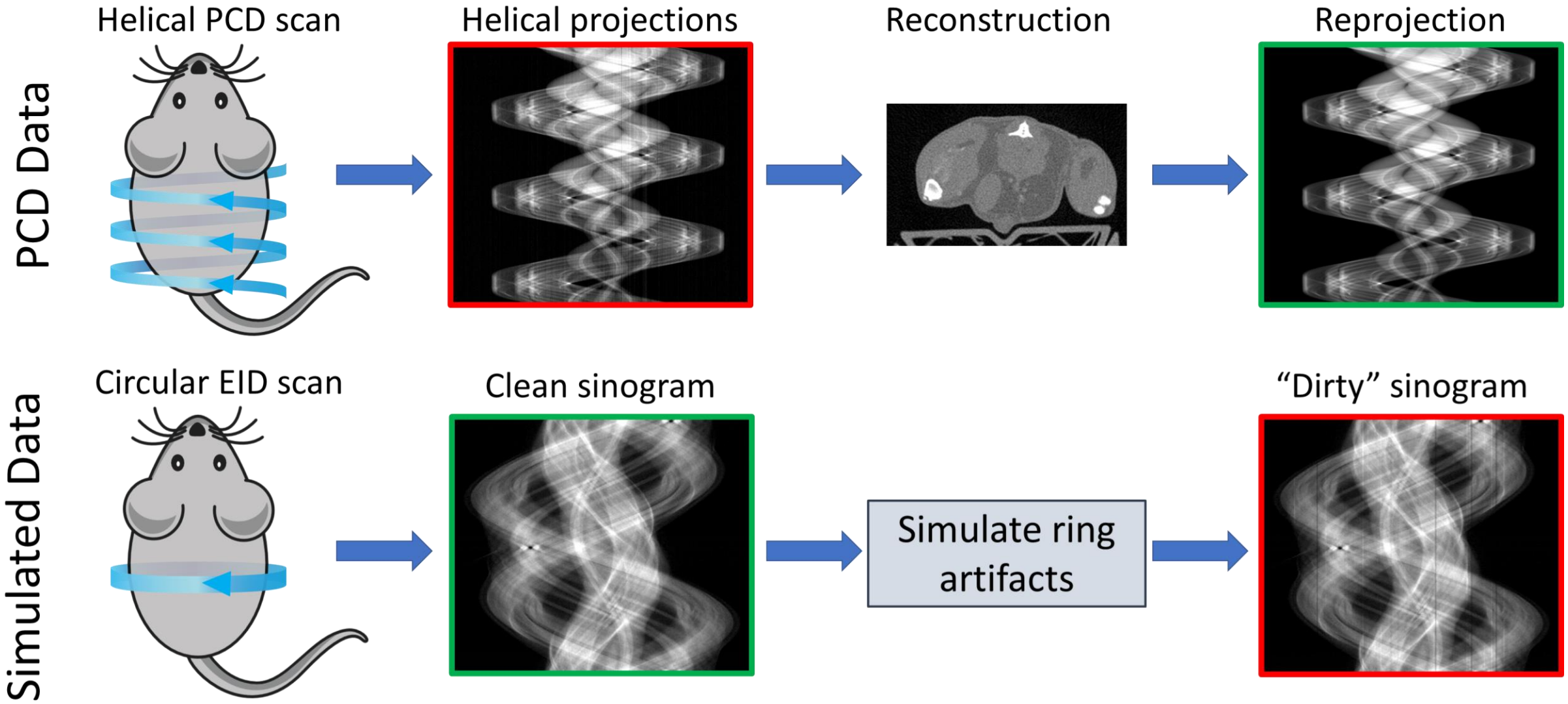


U-Net



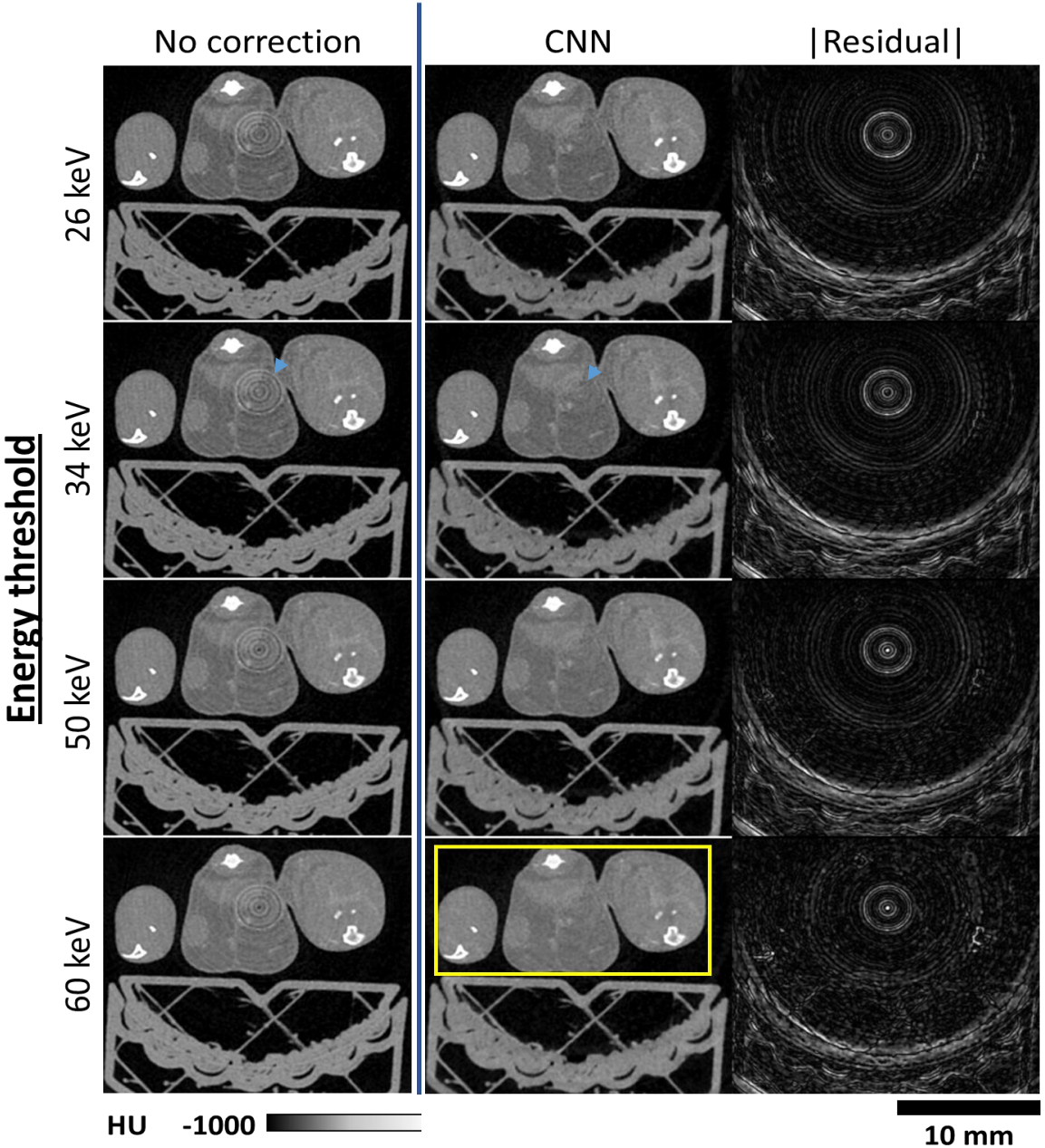
M Holbrook, D. Clark, CT Badea [Ring reduction for micro CT using deep residual learning] - Proc. 5th Int. Conf. Image Formation X-Ray Comput , 2018

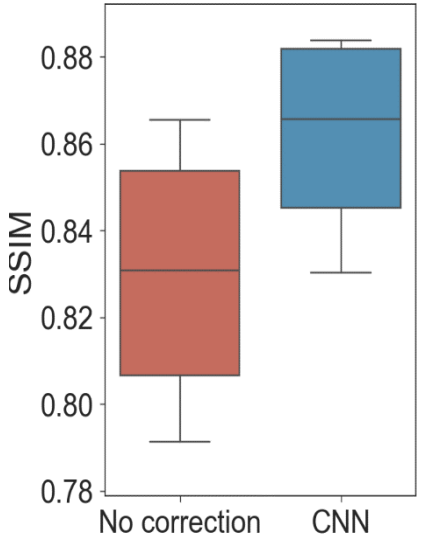
Training Data



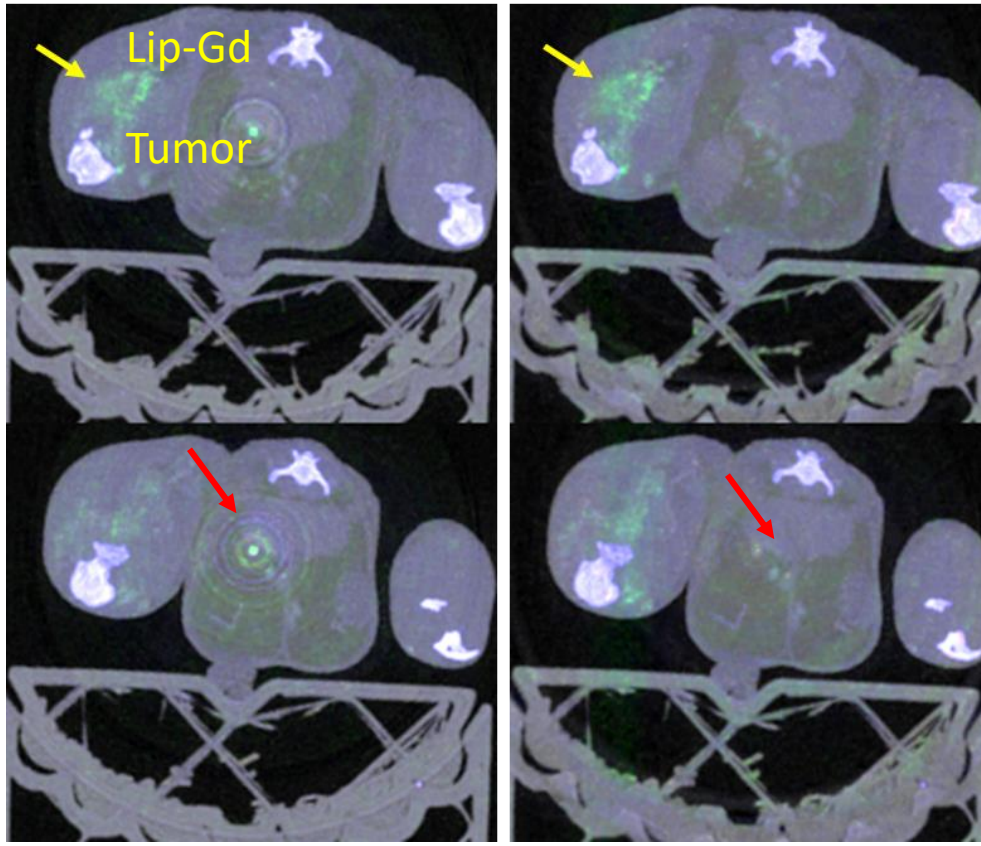
M Holbrook, D. Clark, CT Badea [Ring reduction for micro CT using deep residual learning] - Proc. 5th Int. Conf. Image Formation X-Ray Comput , 2018

Results





Spectral Decomposition



The decomposition separates liposomal Gd (green), photoelectric effect (blue), and Compton scattering (gray).

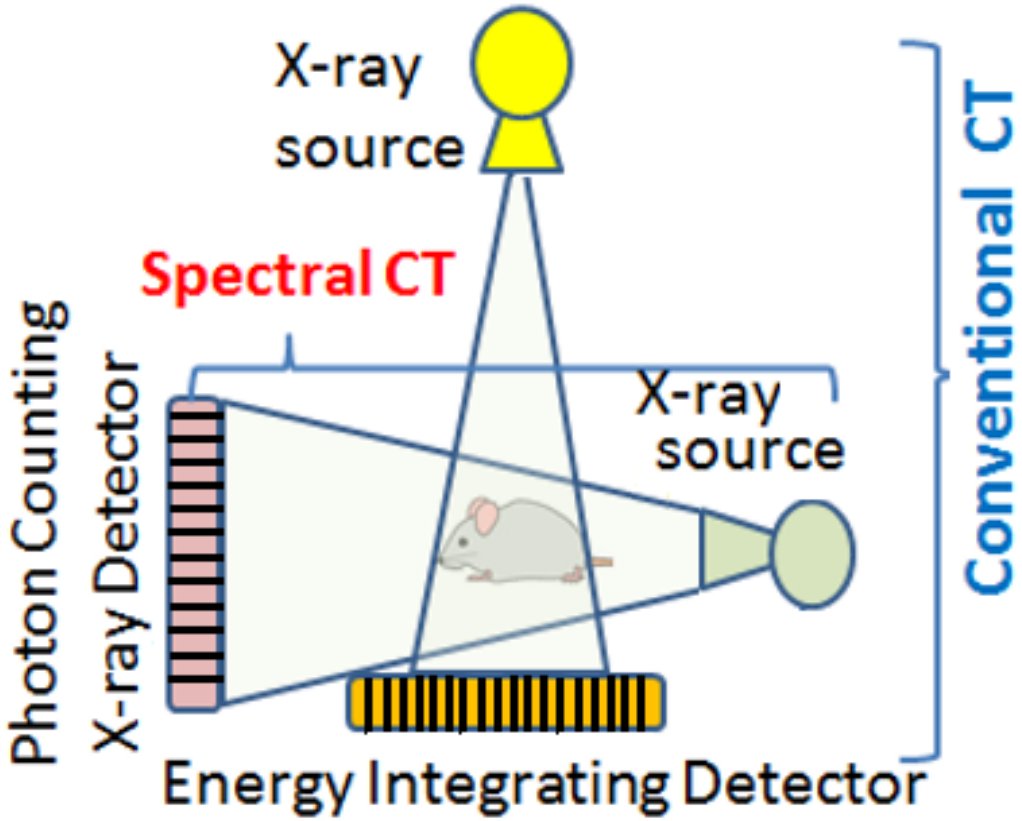
M. Holbrook

DL Case Study 2: Pan Sharpening

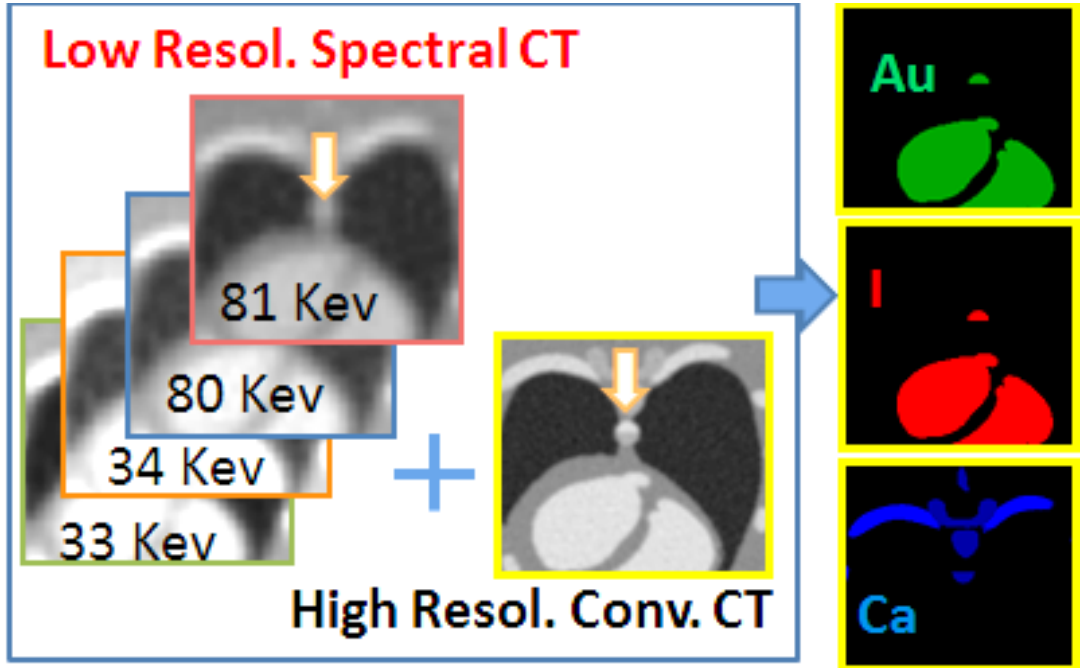
Increasing resolution using DL

Hybrid spectral micro-CT

D. Clark

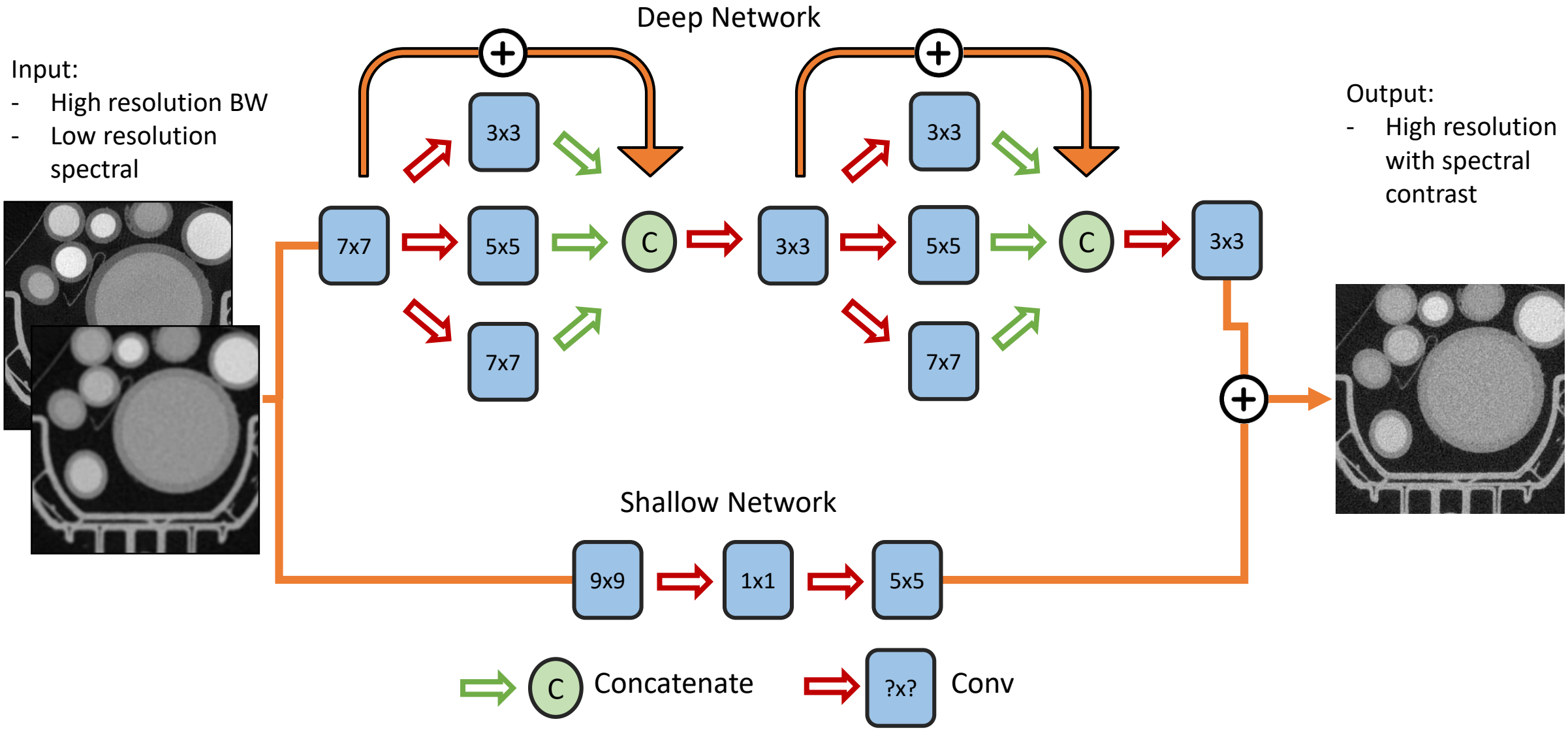


- Pan-Sharpening : Hi res. BW (EID CT) + low res color (PCD, CT)

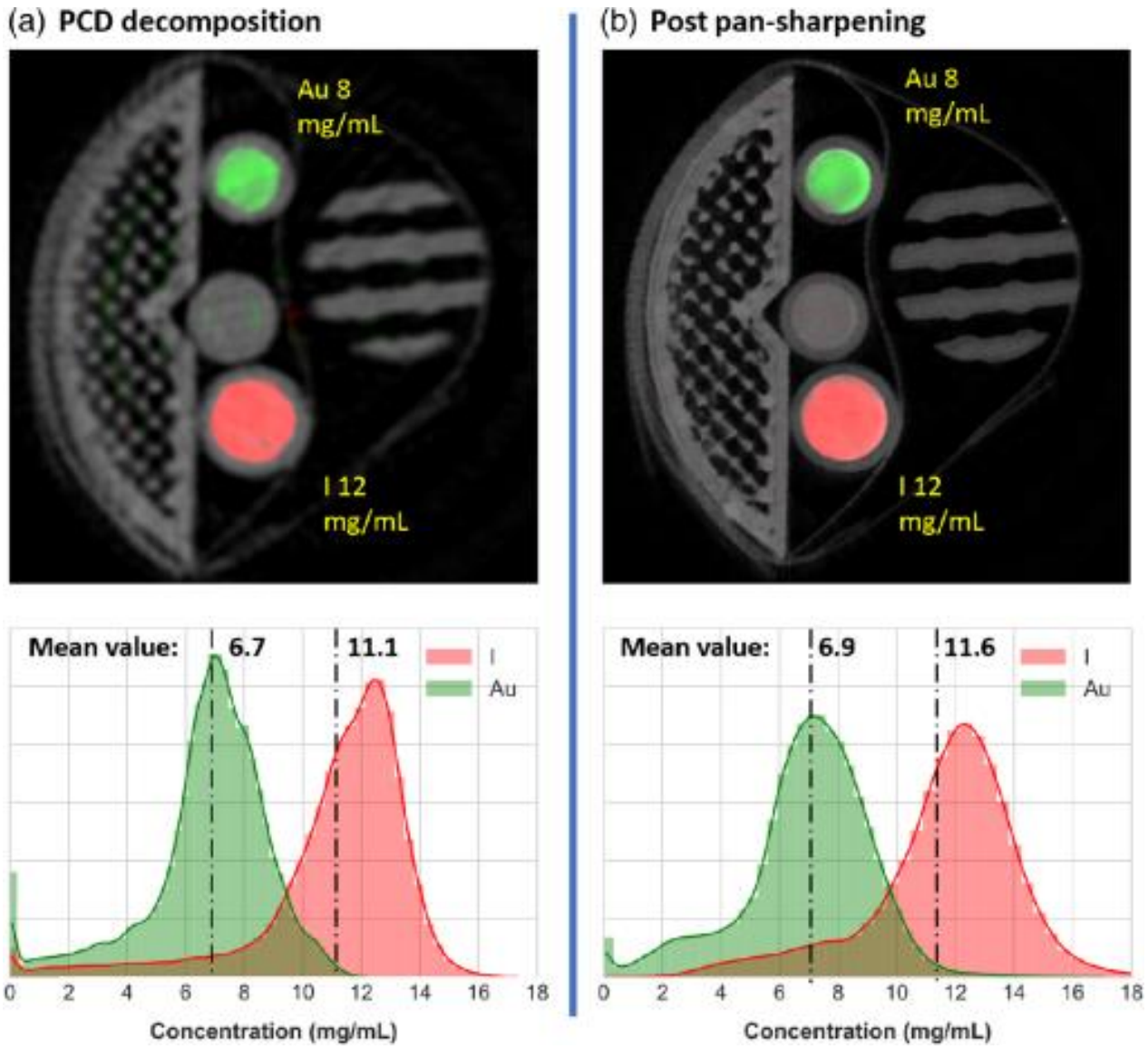


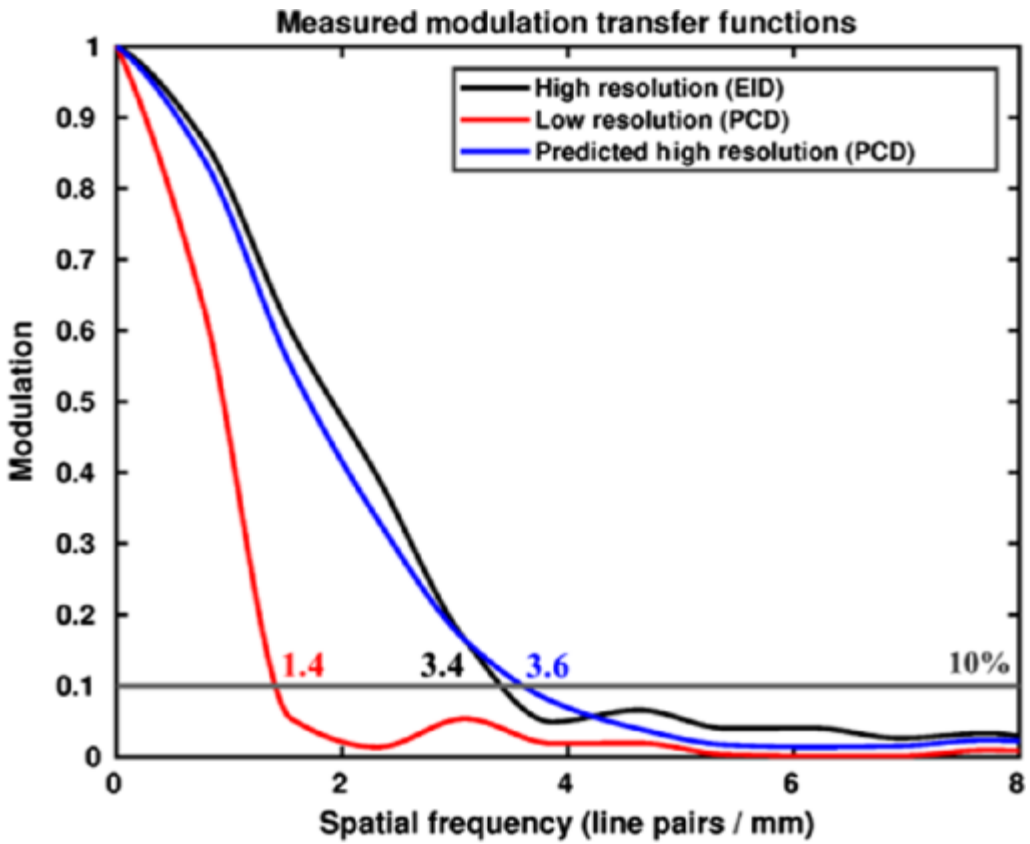
Holbrook, M, et al, J. *Med Imaging* 6, no. 1 (2019): 011004

A CNN for pan sharpening spectral micro-CT



A DL pan sharpening spectral micro-CT: Results

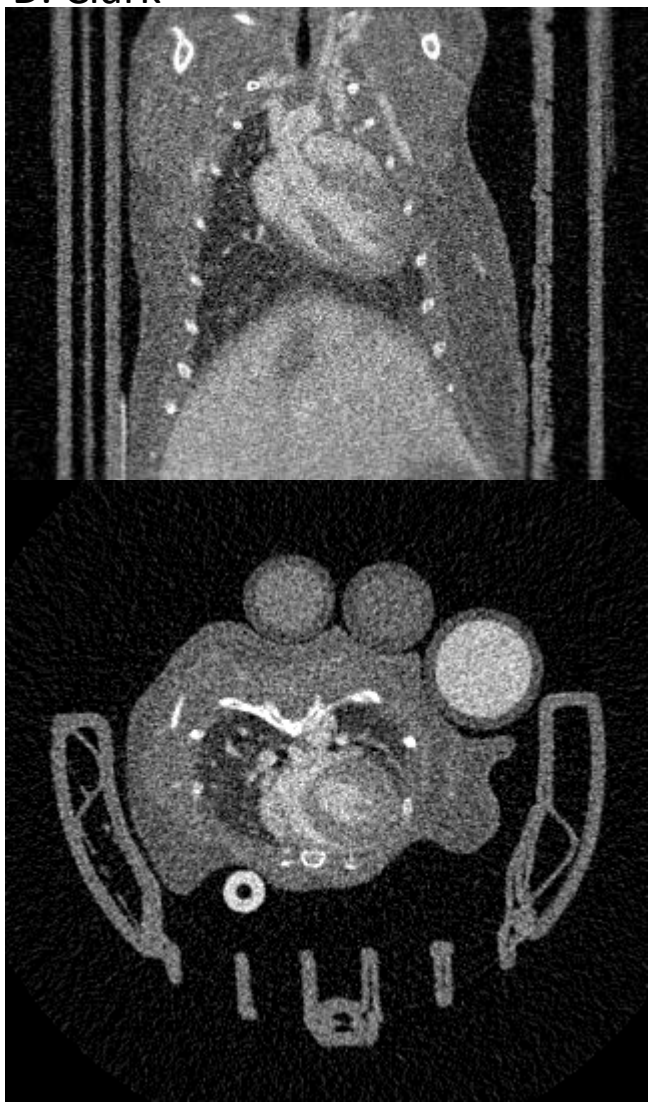




Holbrook, M et al, J. of Medical Imaging, 6(1), 011004 (2019).

D. Clark

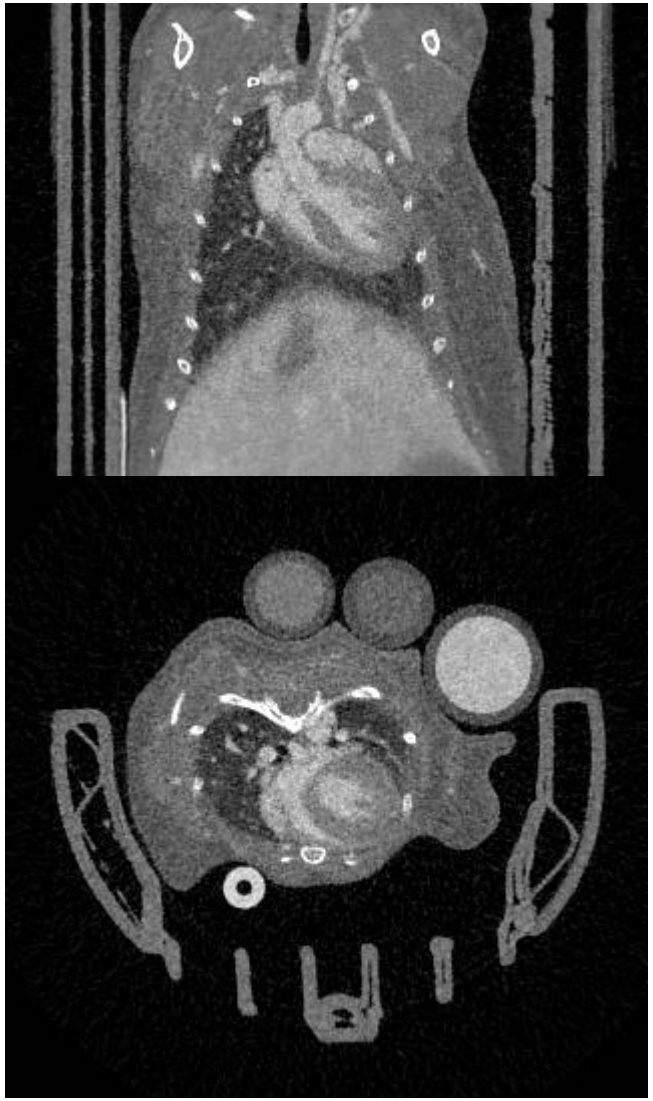
DL Case Study 3: Multi-Channel CT Iterative Reconstruction



Multi-Channel GPU Toolkit

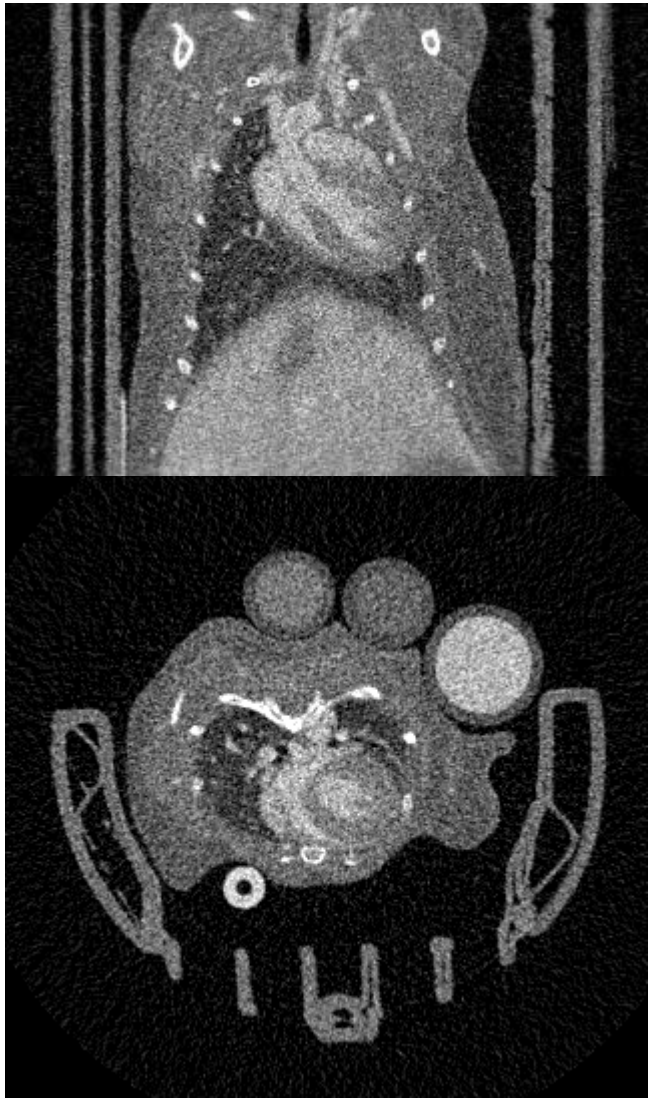
Split Bregman Method

Regularization Model



Clark, D. P., et al . "In *Proceedings of Spie*, Vol. 10948, 2019.

Replacing CT Iterative Reconstruction?



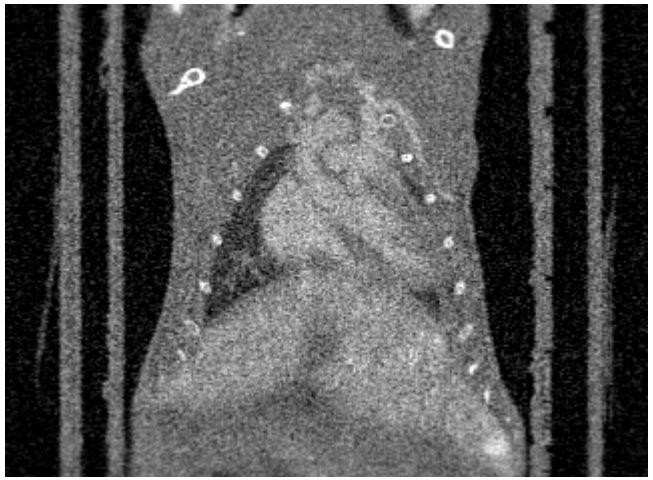
Multi-Channel GPU Toolkit

Split Bregman Method

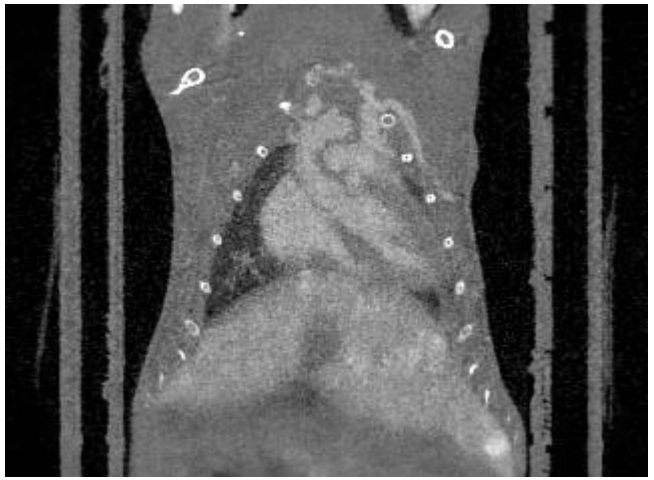
Regularization Model: Deep Learning?

Approach:

- Detector: SANTIS 0804 ME prototype PC x-ray detector
- 9000 projections, over 3x 360° rotations (1.25 cm translation)
- 10 ms exposure / projection (continuous)
- Dose: 190 mGy (fully sampled); voxel size: 123 μm^3

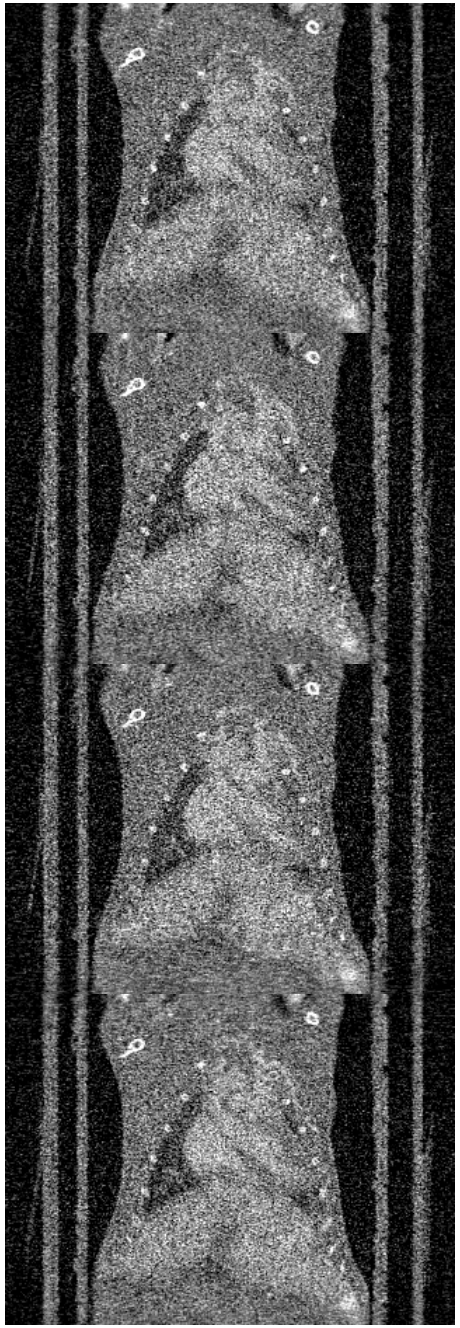


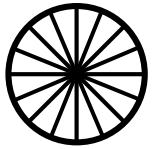
Fully Sampled Reconstruction



Iterative Reconstruction

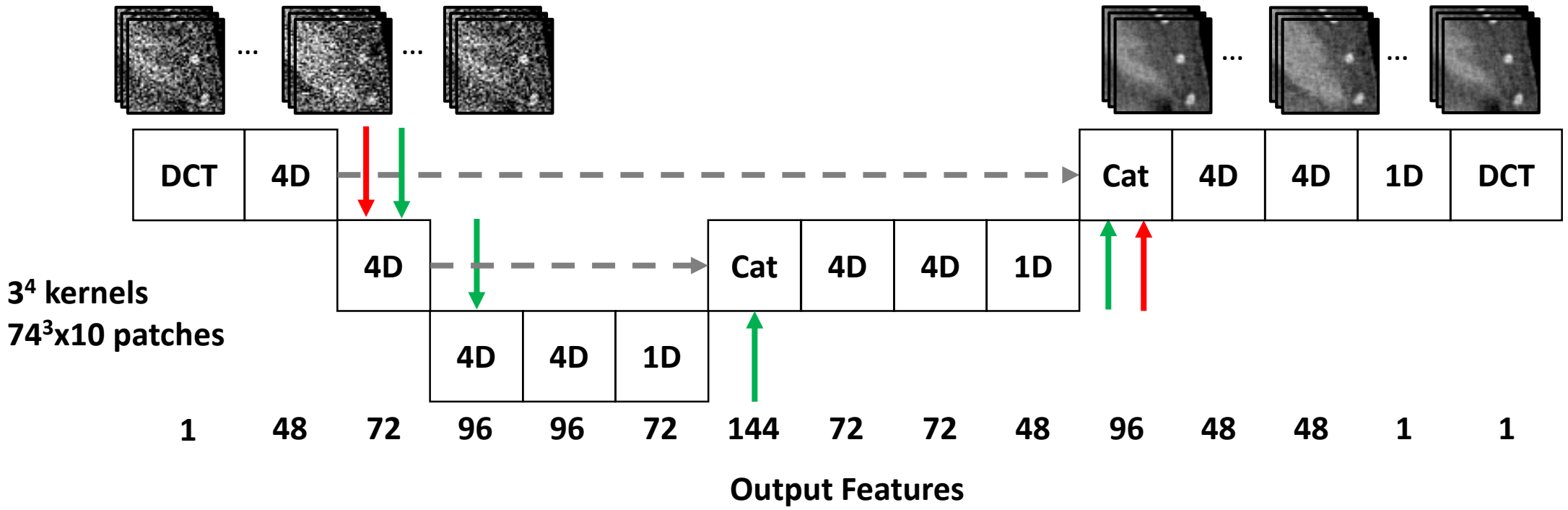
4D CNN





Projection Subsampling

4D CNN: Asymmetric U-Net



4D — 4D Convolution + ReLU

Spatial Max Pooling

Spatial Unpooling

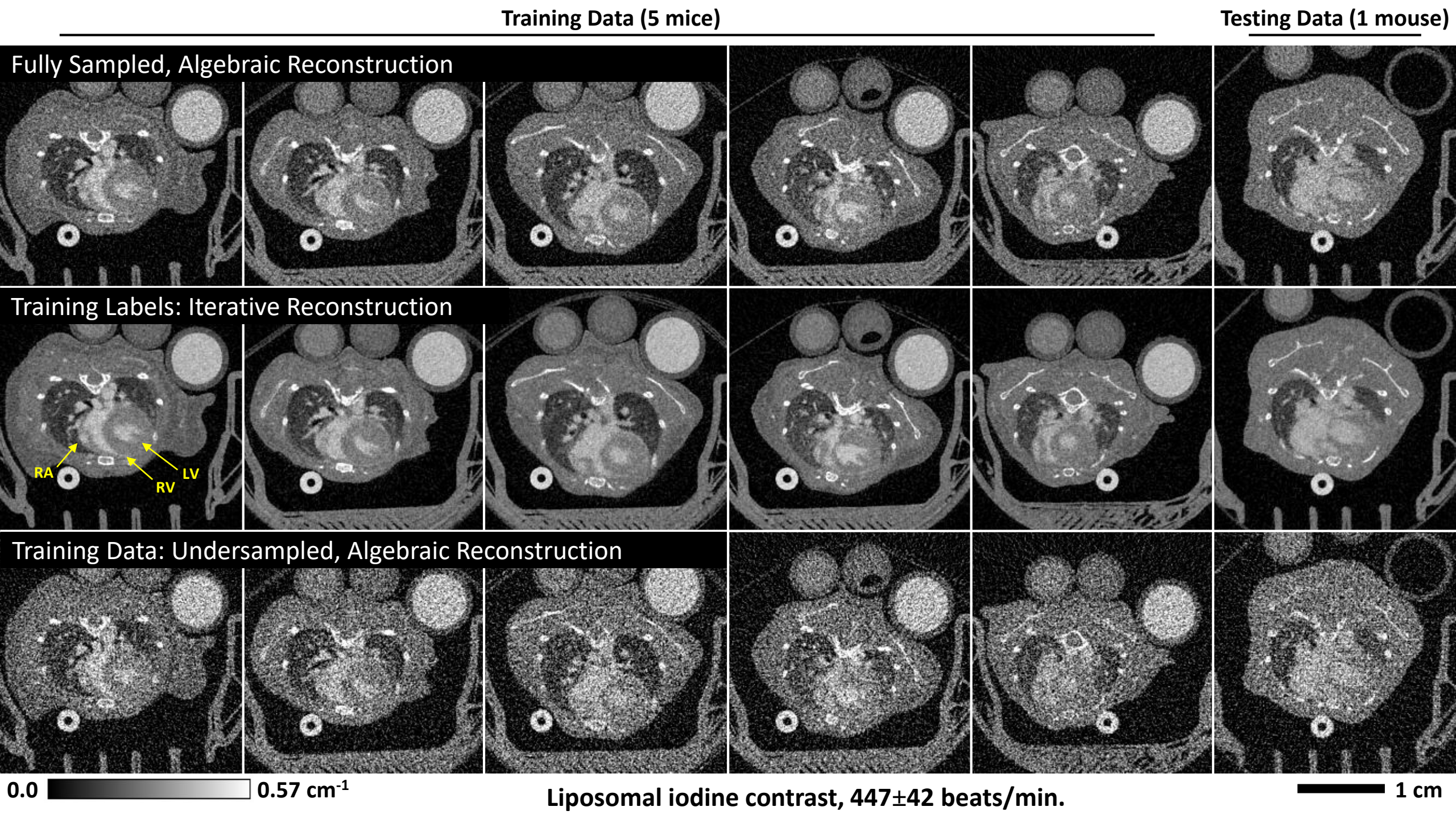
Cat — Skip Connection w/ Cropping & Feature Concatenation

1D — Scalar Convolution + ReLU

Temporal Max Pooling

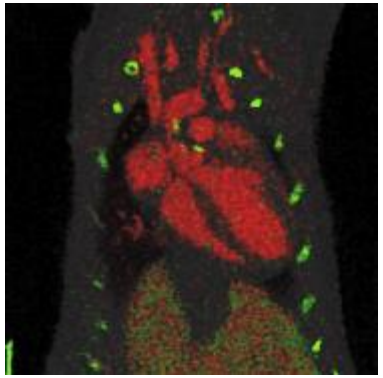
Temporal Unpooling

DCT — Discrete Cosine Transform, Residual Connection



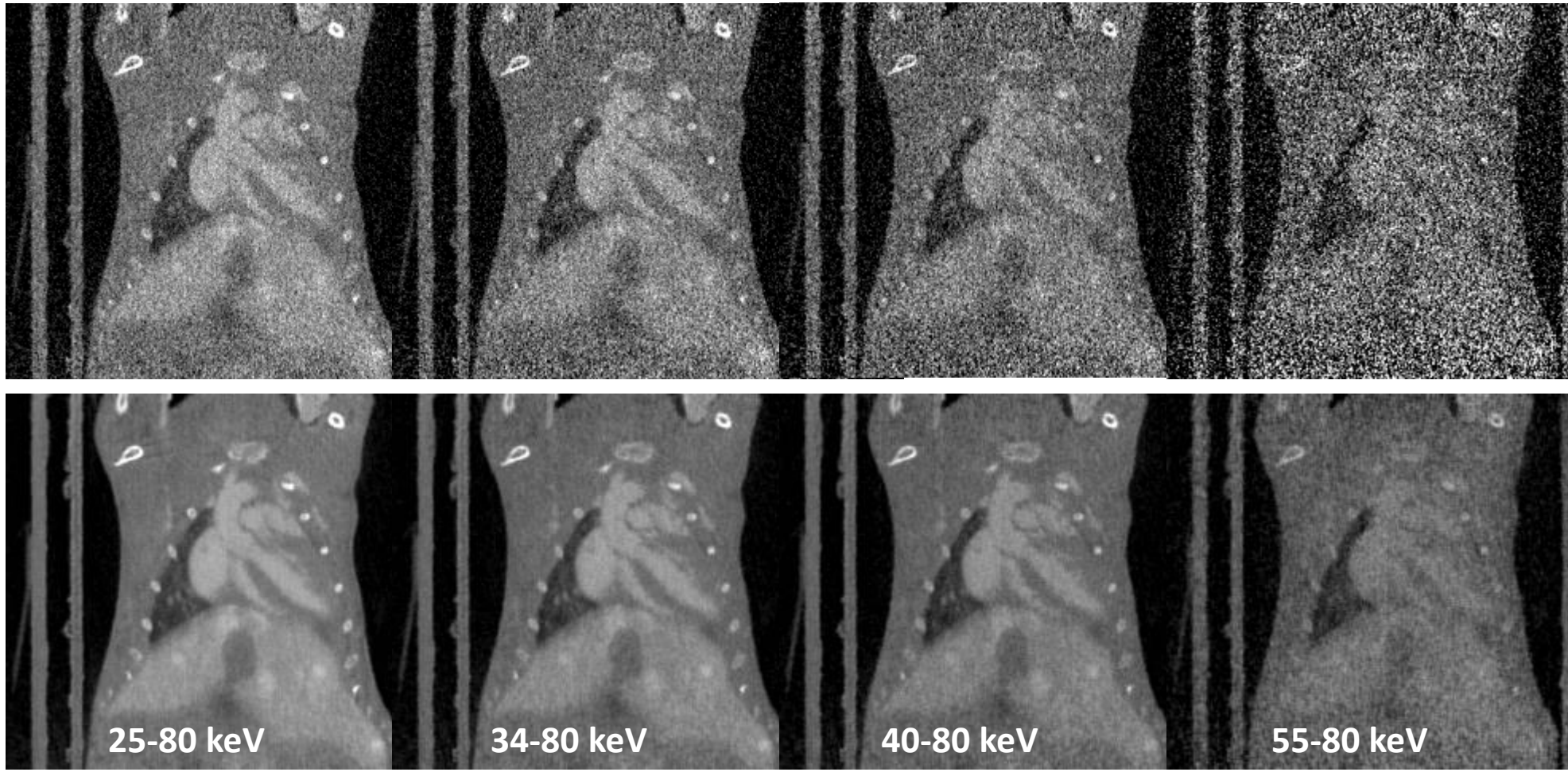
Liposomal iodine contrast, 447±42 beats/min.

5D (3D + Time + Energy) Photon-Counting CT



Iodine, PE, CS Decomposition

CNN Inputs: Analytical Reconstruction



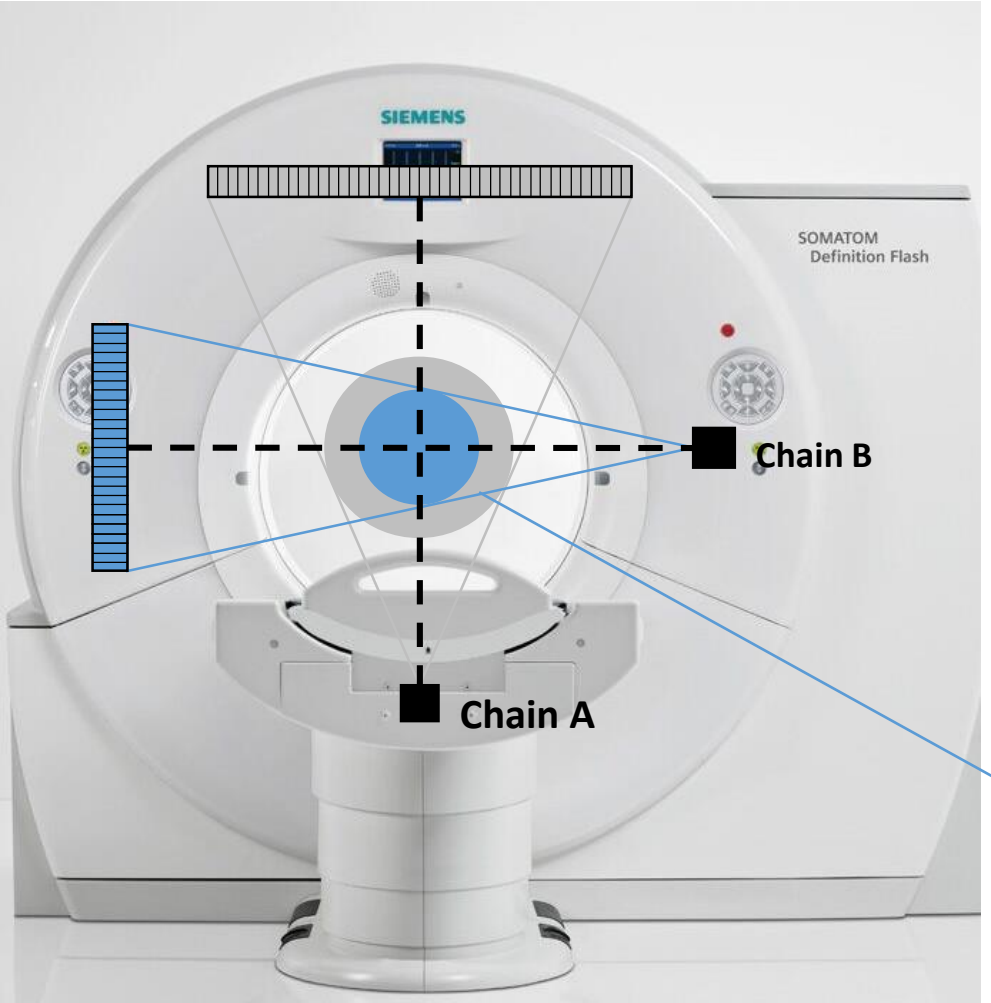
CNN Outputs: single pass w/ 4D CNN

Clark D et al, Plos One, 2019

DL Case Study 4: SPECTRAL EXTRAPOLATION for Clinical Dual Source CT

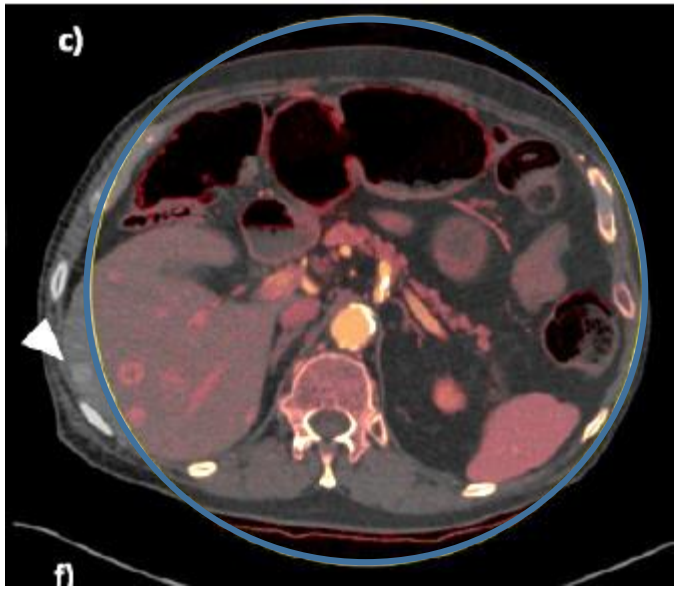
D. Clark

- Data Completion Problem



- Chain A: large FoV, lower energy
- Chain B: small FoV, higher energy

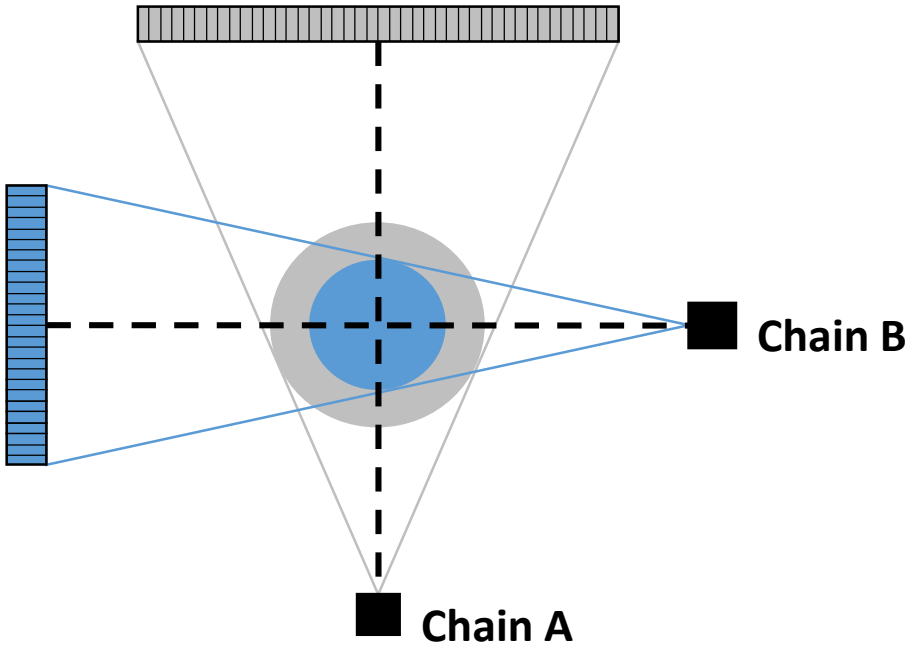
SPECTRAL DECOMPOSITION



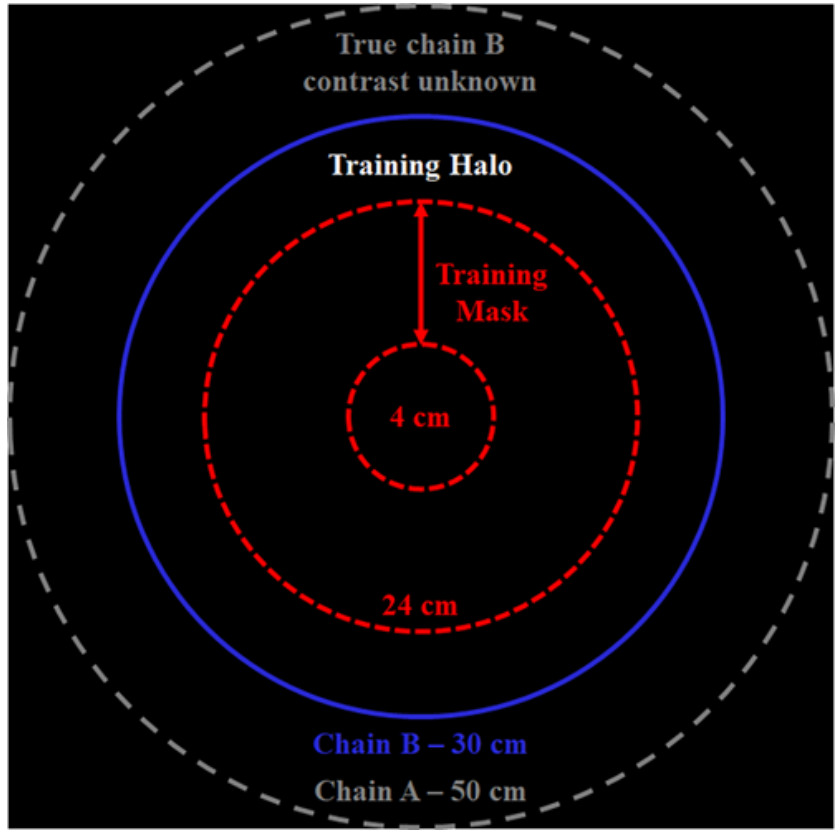
Iodine image

Task: Can we recover Spectral Information in the Gray area?

Deep learning based spectral extrapolation for dual-source, dual-energy x-ray computed tomography



Chain A: large FoV, lower energy
Chain B: small FoV, higher energy

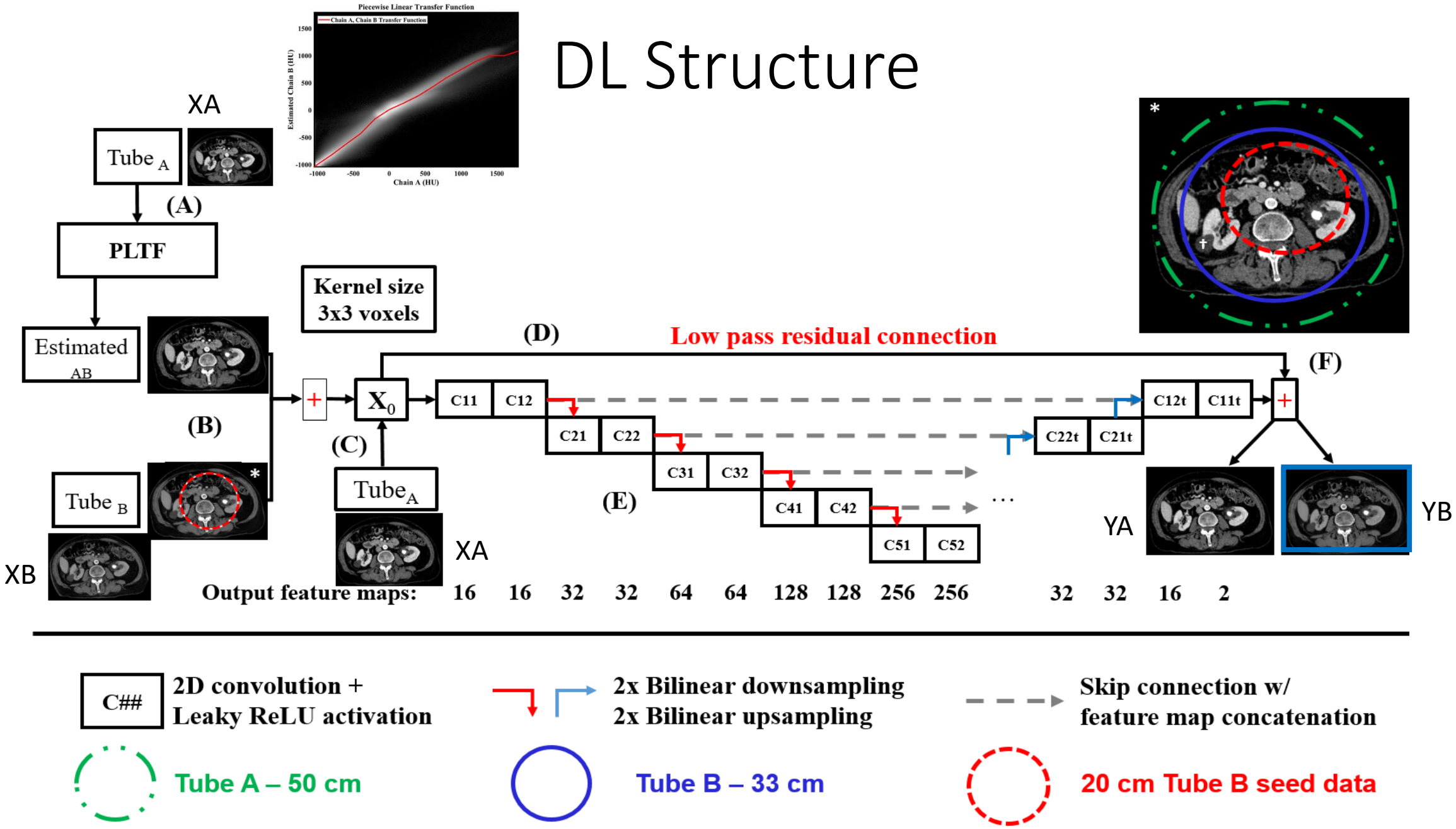


Spectral extrapolation training and testing strategy

-50 patient data sets, each reconstructed with 0.75-mm slices, averaged to produce 3-mm thick slices,
-training, validation, and testing. (40/5/5)

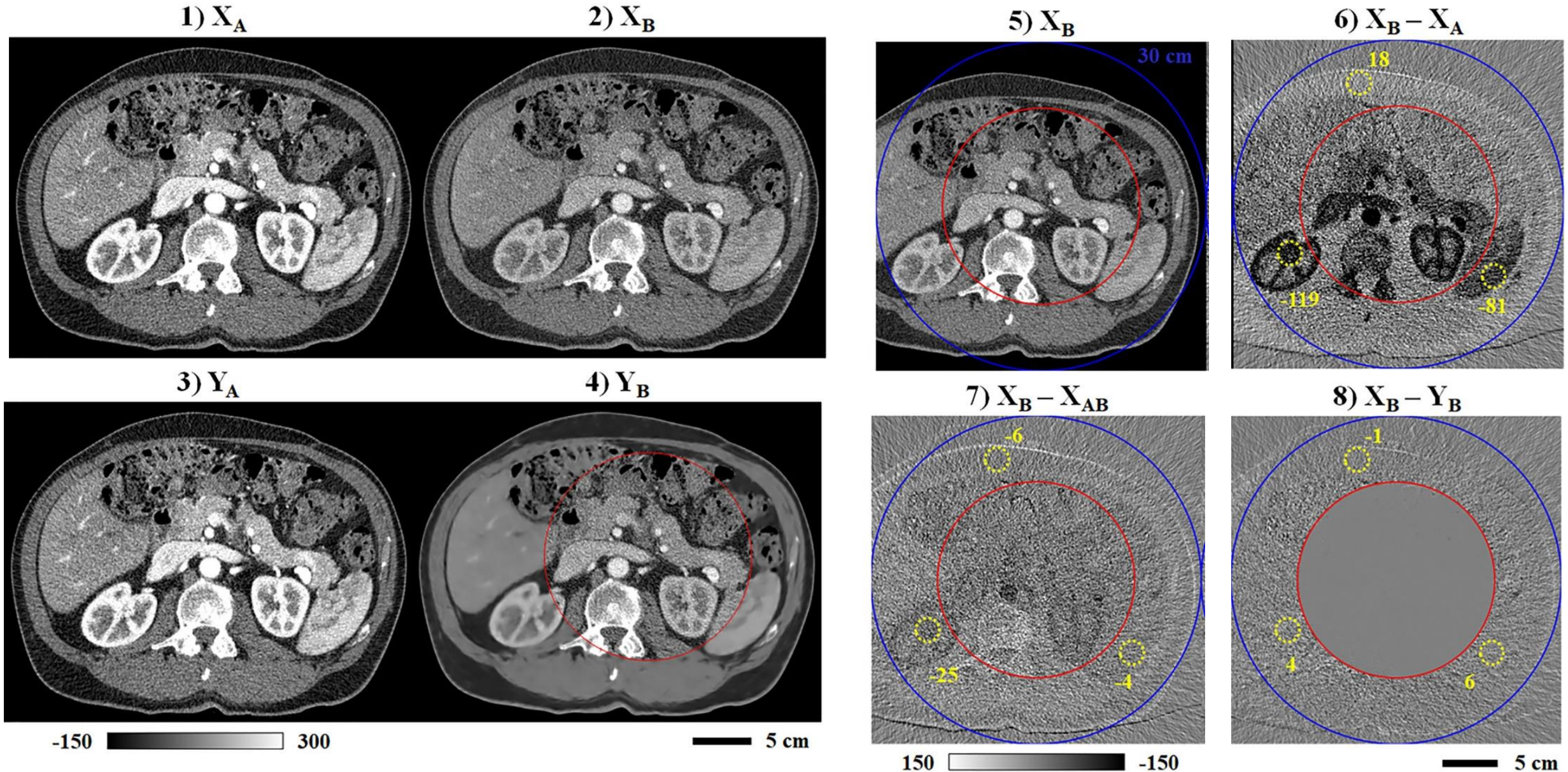
DP Clark,et al. Medical Physics 47 (9), 4150-4163 (2020)

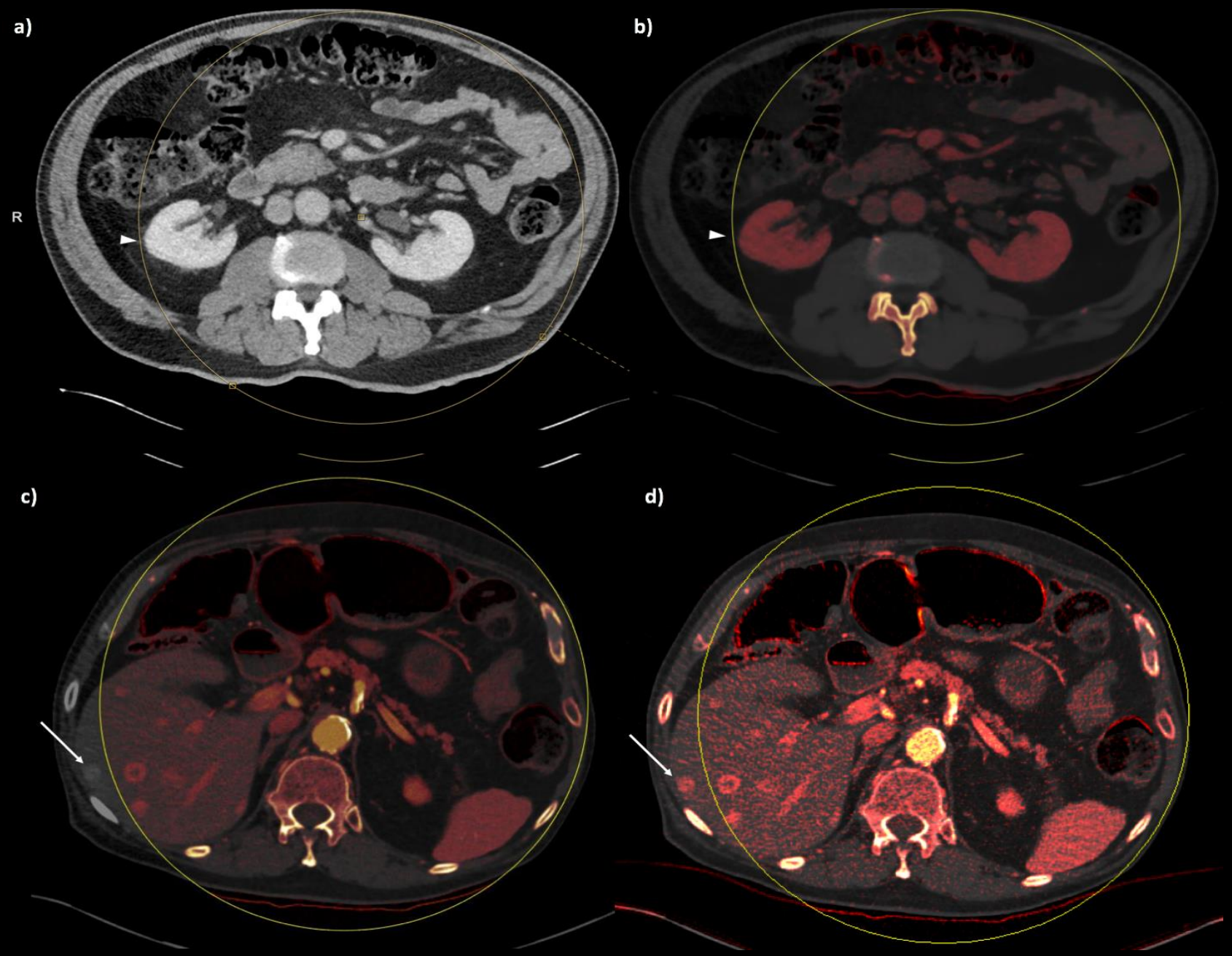
DL Structure



DP Clark,et al. Medical Physics 47 (9), 4150-4163 (2020)

Results


1) X_A
2) X_B
3) Y_A
4) Y_B
-150
300
5 cm
5) X_B
30 cm
6) $X_B - X_A$
18
-119
-81
7) $X_B - X_{AB}$
-6
-25
-4
8) $X_B - Y_B$
-1
4
6
150
-150
5 cm


a)
b)
R
c)
d)

Conclusions

- DL can help spectral CT with reducing artifacts and noise, improving image resolution, or extrapolating spectral information.
- DL solutions are robust but require fixed protocols and reproducible image quality.
- DL approaches can provide high-throughput in preclinical imaging in co-clinical trials.

D. Clark, PhD

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Y. Qi , MD

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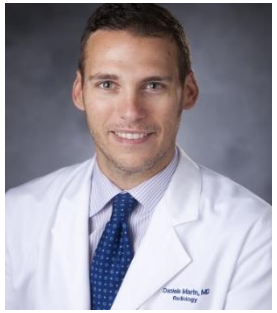
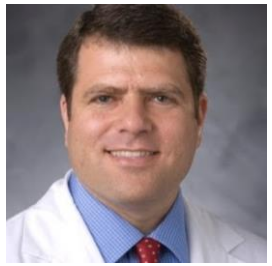


D. Marin, MD

FR Schwartz , MD



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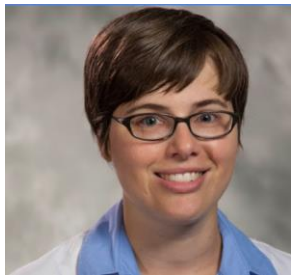

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