25th International Workshops on Radiation Imaging Detectors

Imaging methods for in-vivo BNCT by using Compton camera type detector

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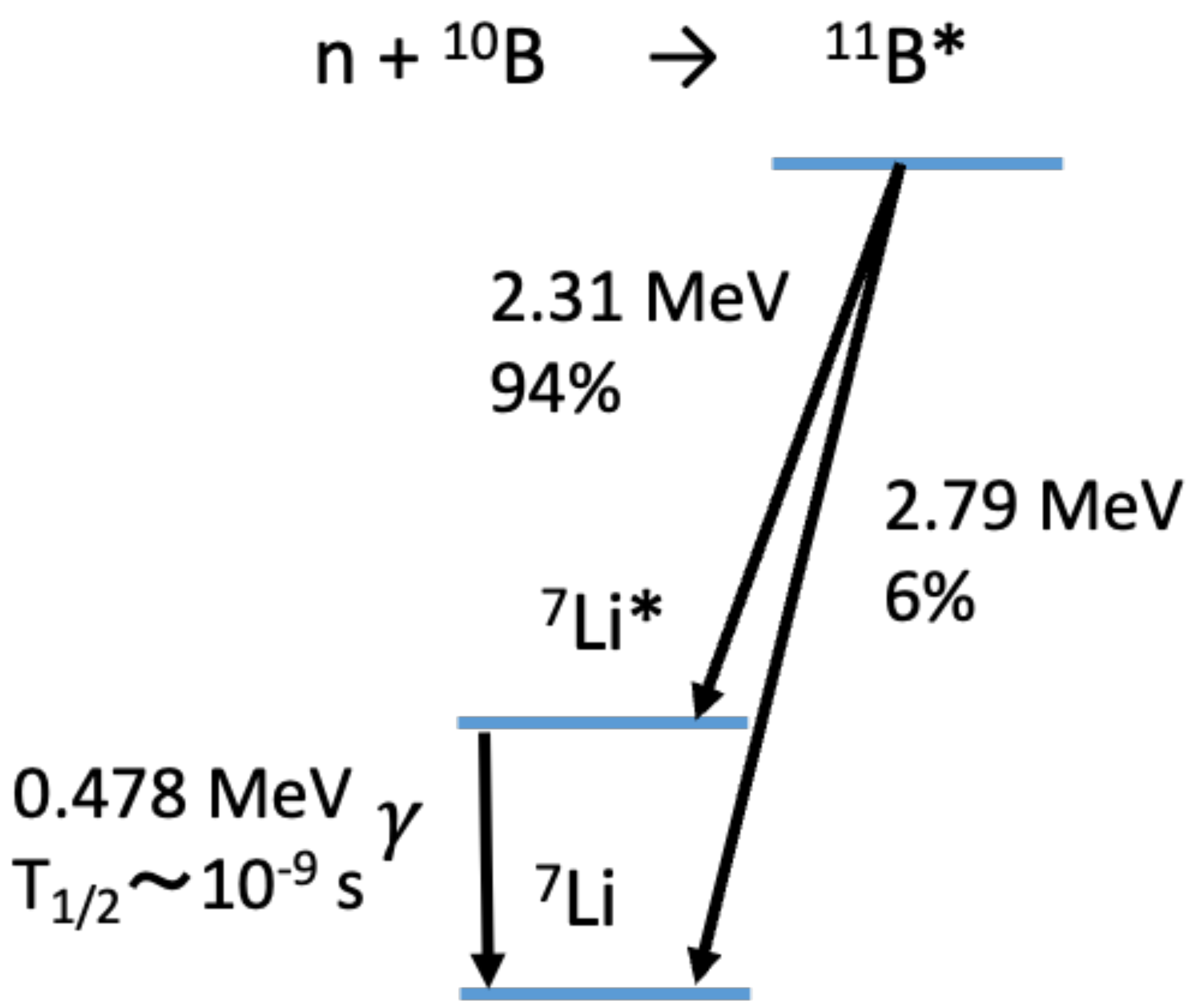
Outline

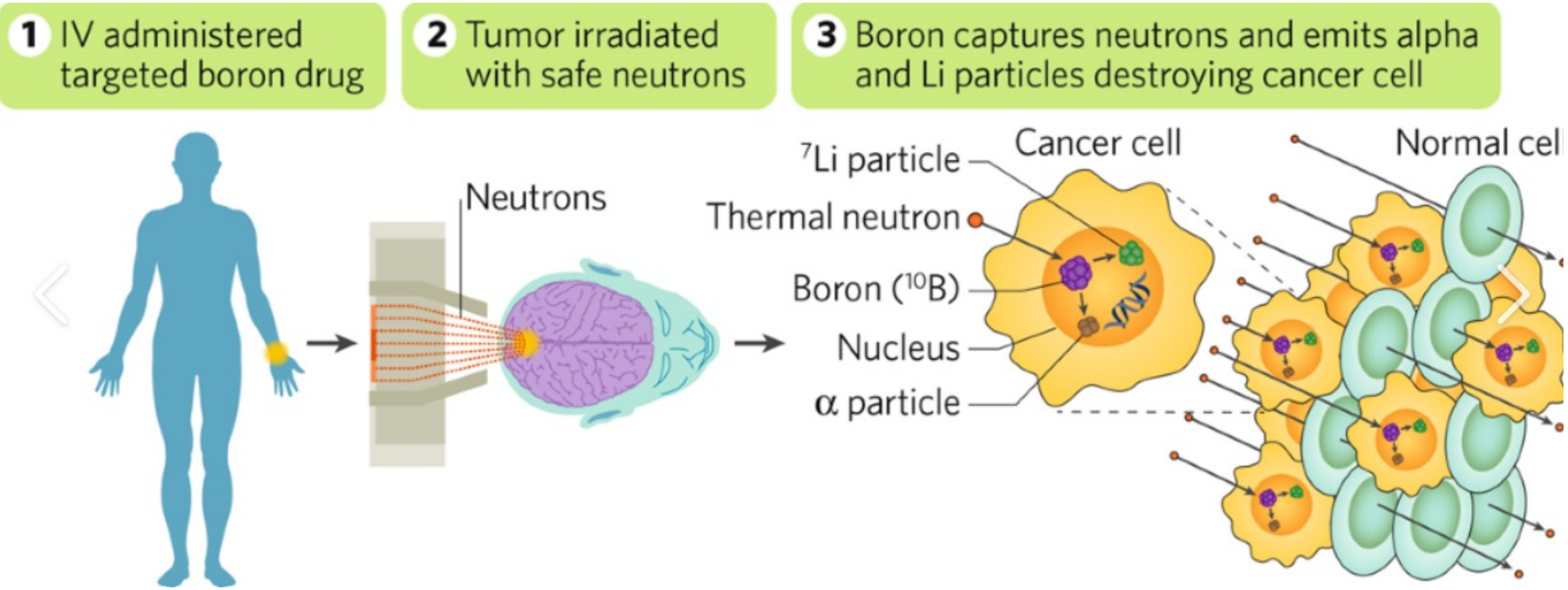
- Boron Neutron Capture Therapy bases and dosimetry
- Compton imaging principles
- First Monte Carlo simulations
- Classic approach by using tomography iteratives algorithms
- Novel approach by Deep Learning (DL) models

Boron neutron capture therapy

Boron Neutron Capture Therapy (BNCT) is an innovative hadrontherapy with high selectivity over cancer tissue based on the neutron capture reaction $^{10}B(n, \alpha)7Li$



	Energy (MeV)	Range (µm)
α	1.47-178	9-11
^{7}Li	0.84-101	4-5
γ	0.48	



- Dose distribution: $dD(x,y,z) \approx n_{^{10}B}(x,y,z)\ \Phi(x,y,z)\ dV$
- Reaction products range < cell dimensions (≈ 10 µm) → **high selectivity**
- Tumor-to-healthy boron concentration ratio (T/N) > 3*.

*Skwierawska, D. et. al. Clinical Viability of Boron Neutron Capture Therapy for Personalized Radiation Treatment. Cancers 2022, 14, 2865.

Dosimetry on BNCT and project scope

- Main nuclear interactions that contribute to the BNCT total dose delivery:

D_{total} =

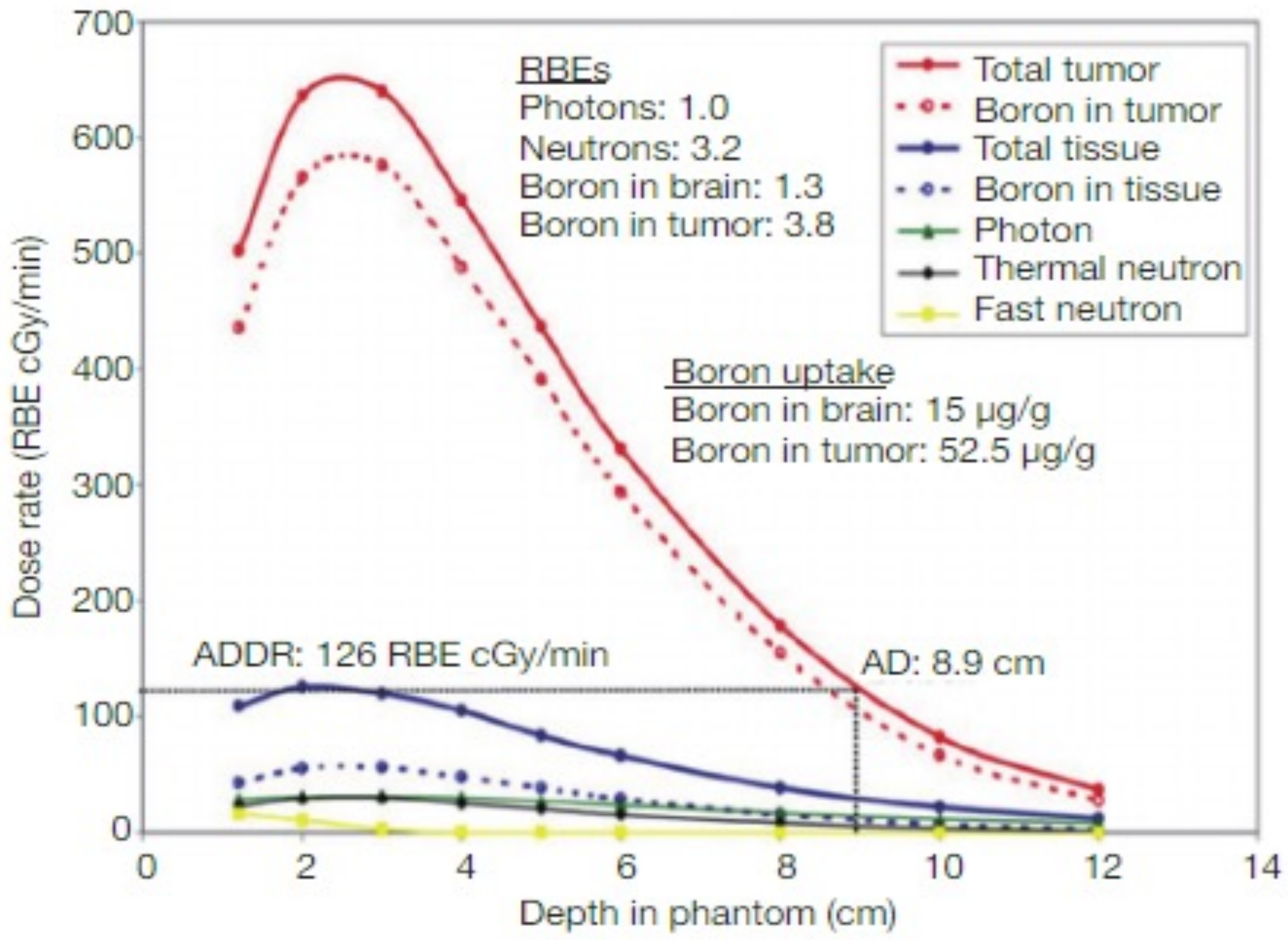
D_B + Therapeutic dose from $^{10}B(n,\alpha)^7Li$ (σ=3837 b)

D_p + From $^{14}N(n,p)^{14}C$ reactions (Ep=630 keV, σ=1.9 b) due to thermal neutron

D_n + Due to epithermal and fast neutron elastic scattering daily with H nuclei

D_γ From $^1H(n,\gamma)^2H$ (E=2.2 MeV, σ=0.33 b) & reactor background

→ Therapeutic boron dose as main dose contributor.



Altieri S, Protti N. A brief review on reactor-based neutron sources for boron neutron capture therapy. Ther Radiol Oncol 2018;2:47.

Nowadays dose estimation by blood test before, meanwhile and after irradiation and Monte Carlo estimation

Project aims to develop an **on-line dose estimation method by using Compton imaging**

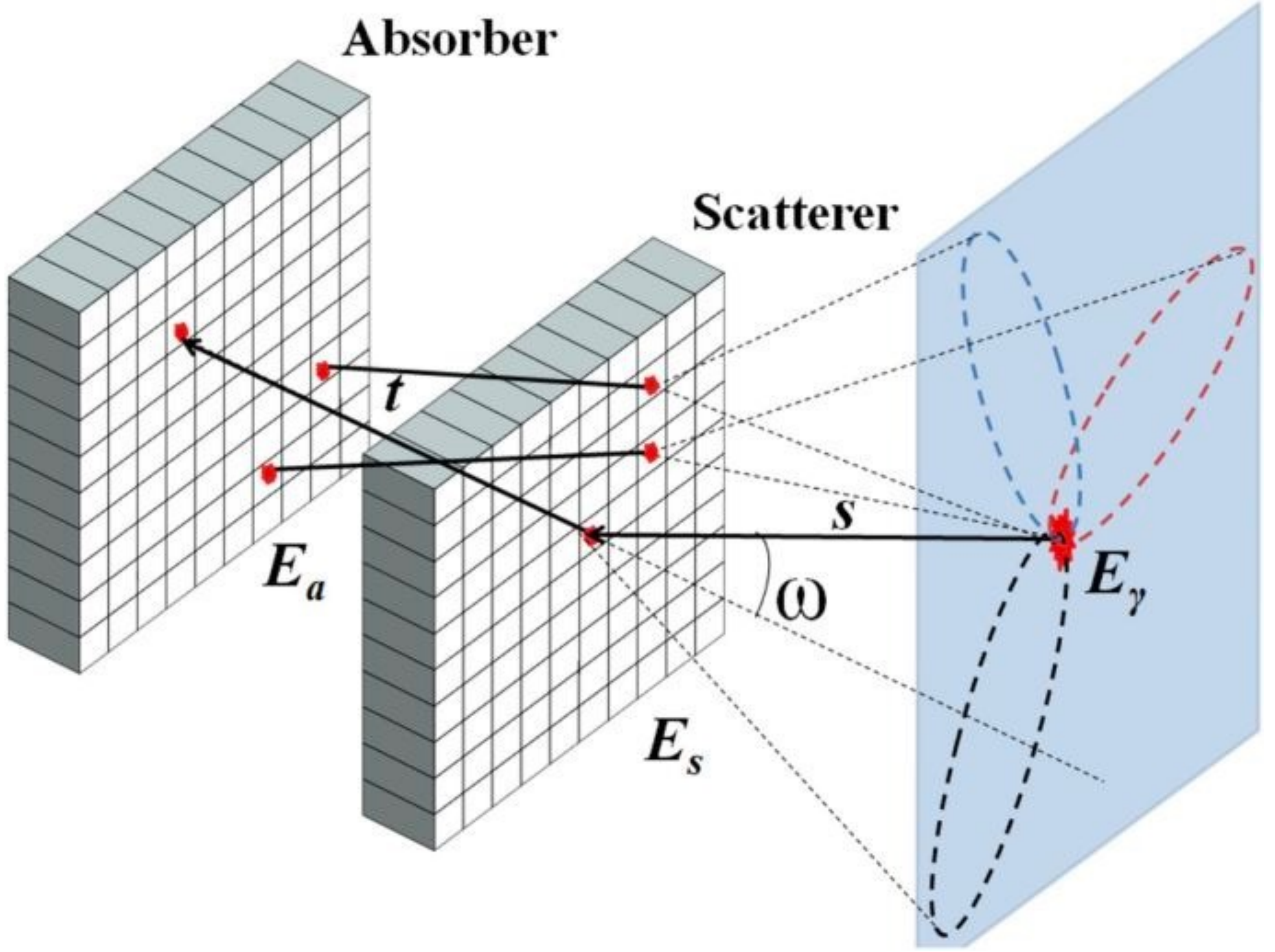
Compton imaging method

- **Principle**

$$cos(\theta) = 1 - m_e c^2 \left(\frac{1}{E_a} - \frac{1}{E_\gamma}\right)$$

where $E_\gamma = E_s + E_a$

→ Compton event: the position of the source is confined in the Compton cone and found by overlapping them

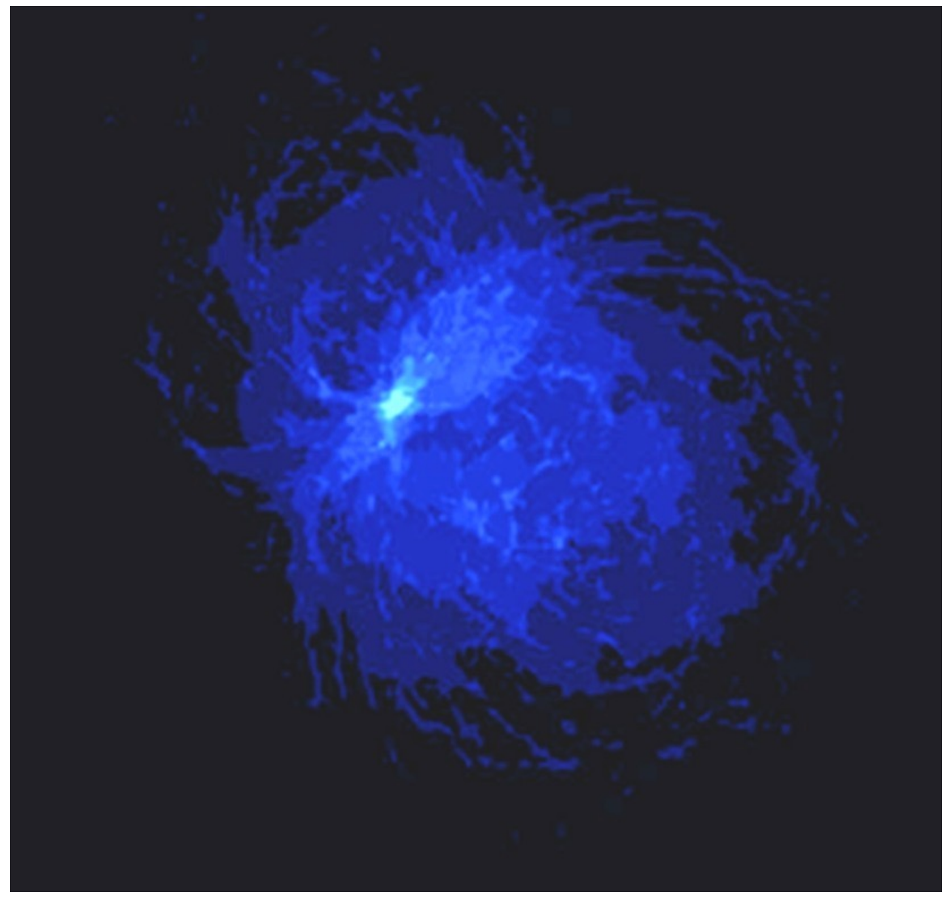


- **Single stage Compton imaging or "True events"**

good events don't include multiscattering Compton

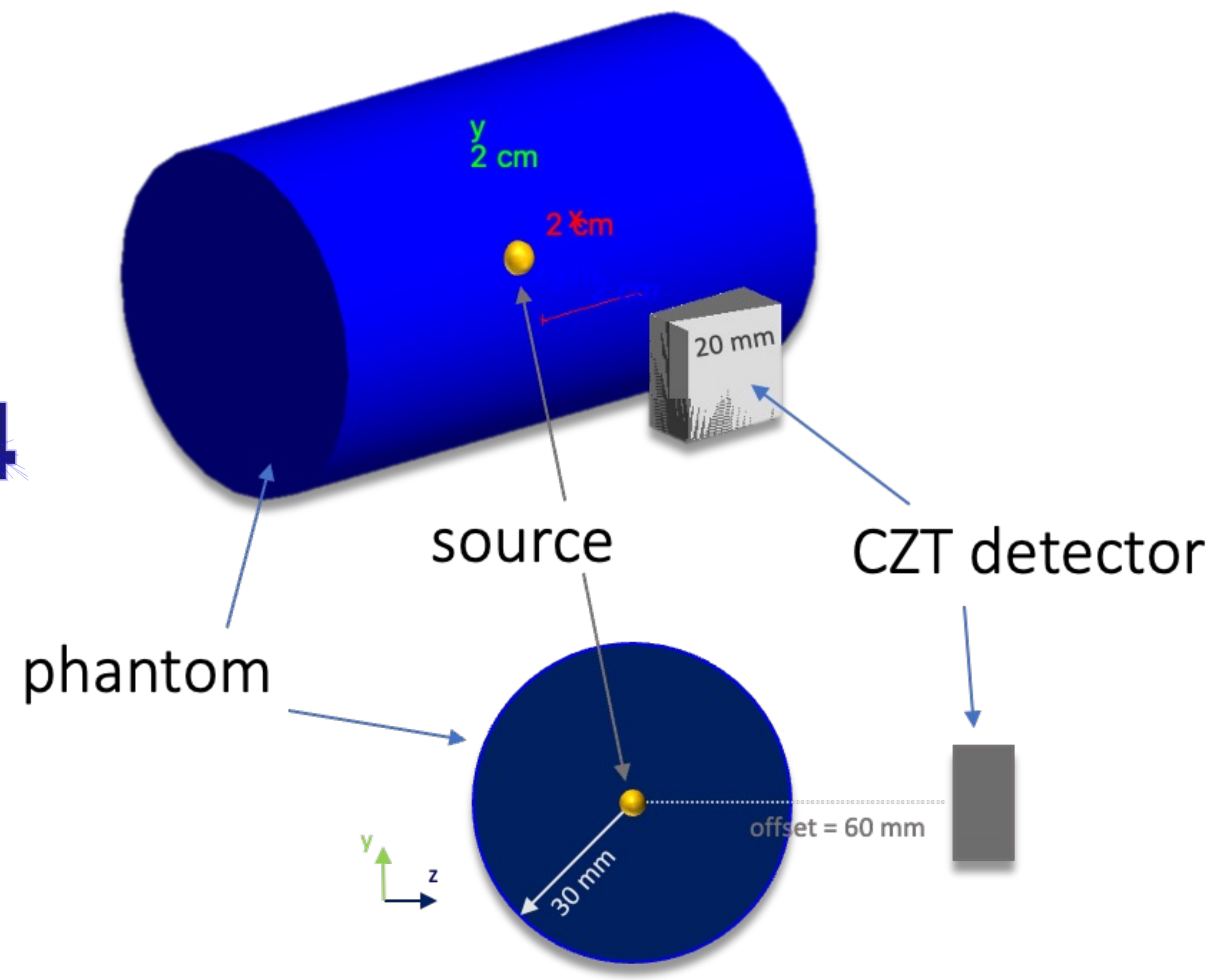
- **Main advantages**

3D Imaging Capability, High Sensitivity, large Field of View → Compact detection systems

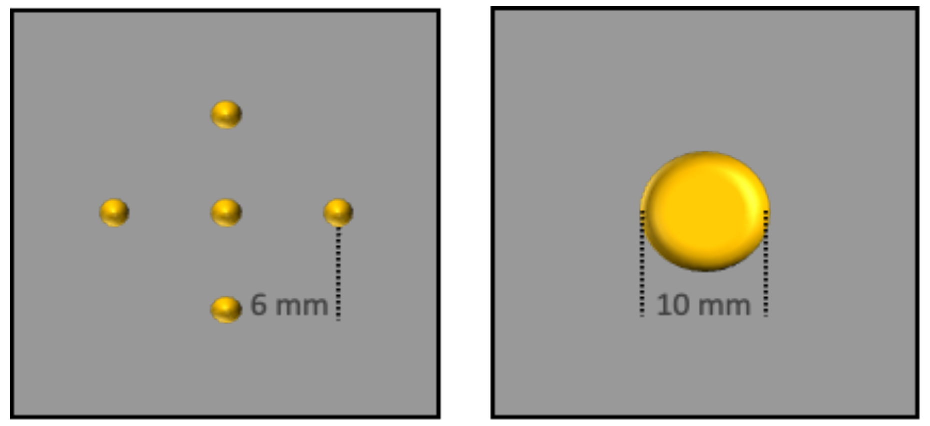


Backward projection example

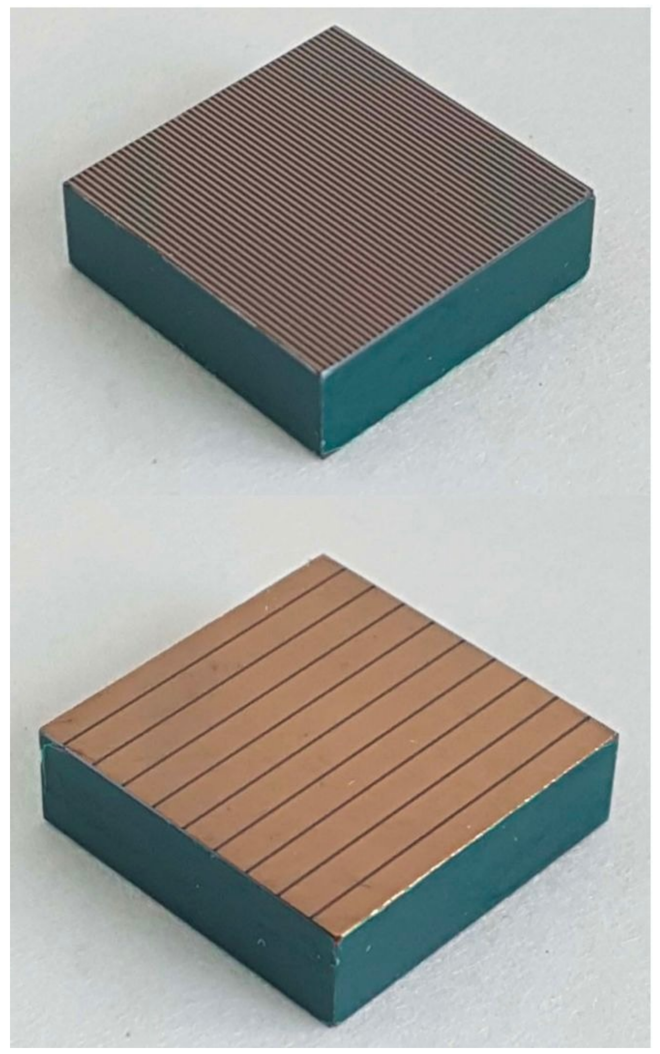
First simulation set-up



- Detector: CZT crystal stack (5 mm thickness each), 60 mm from the source
- Phantom material: Air, soft tissue
- Simulated sources: 5-points like and spheric 478 keV gamma distributions

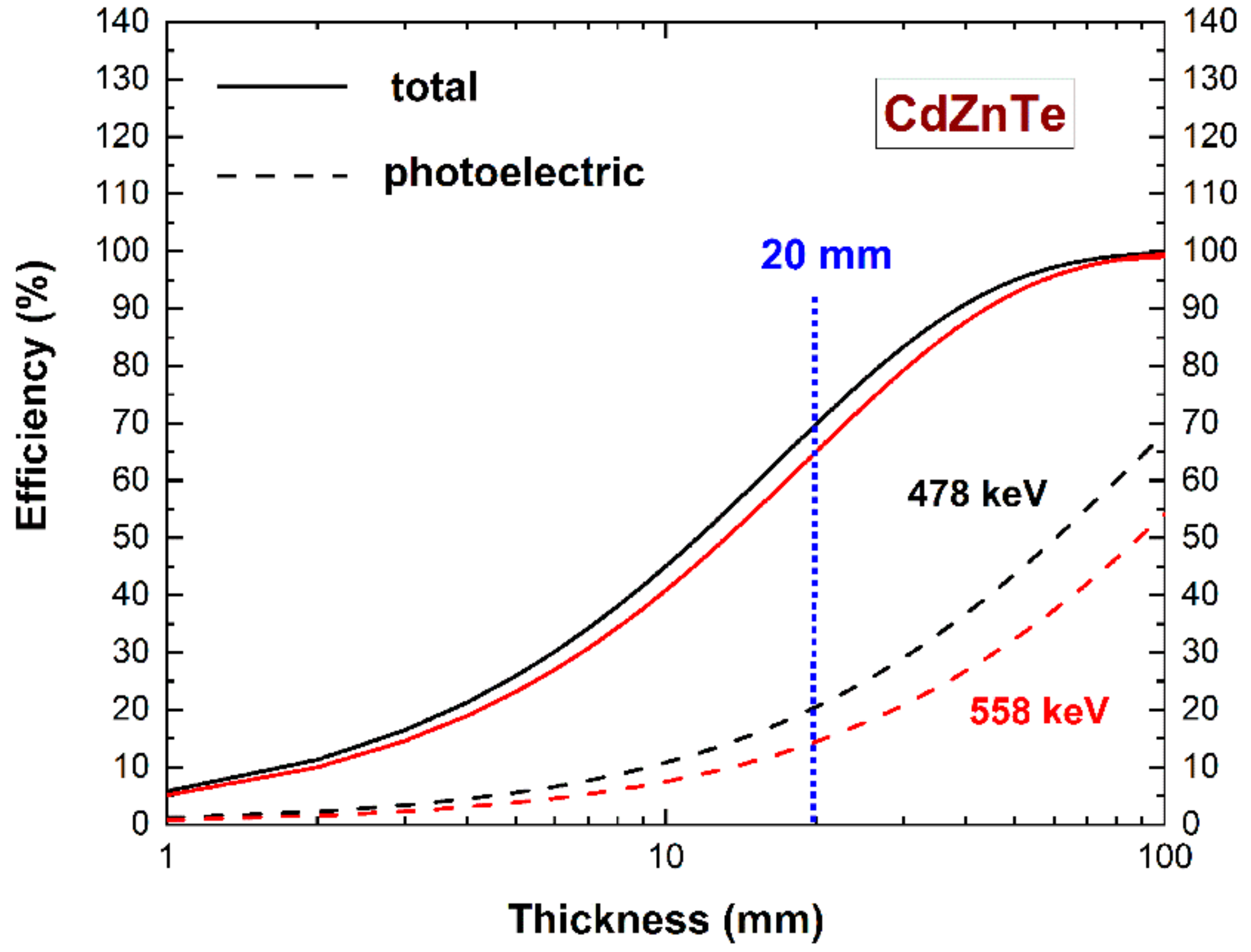


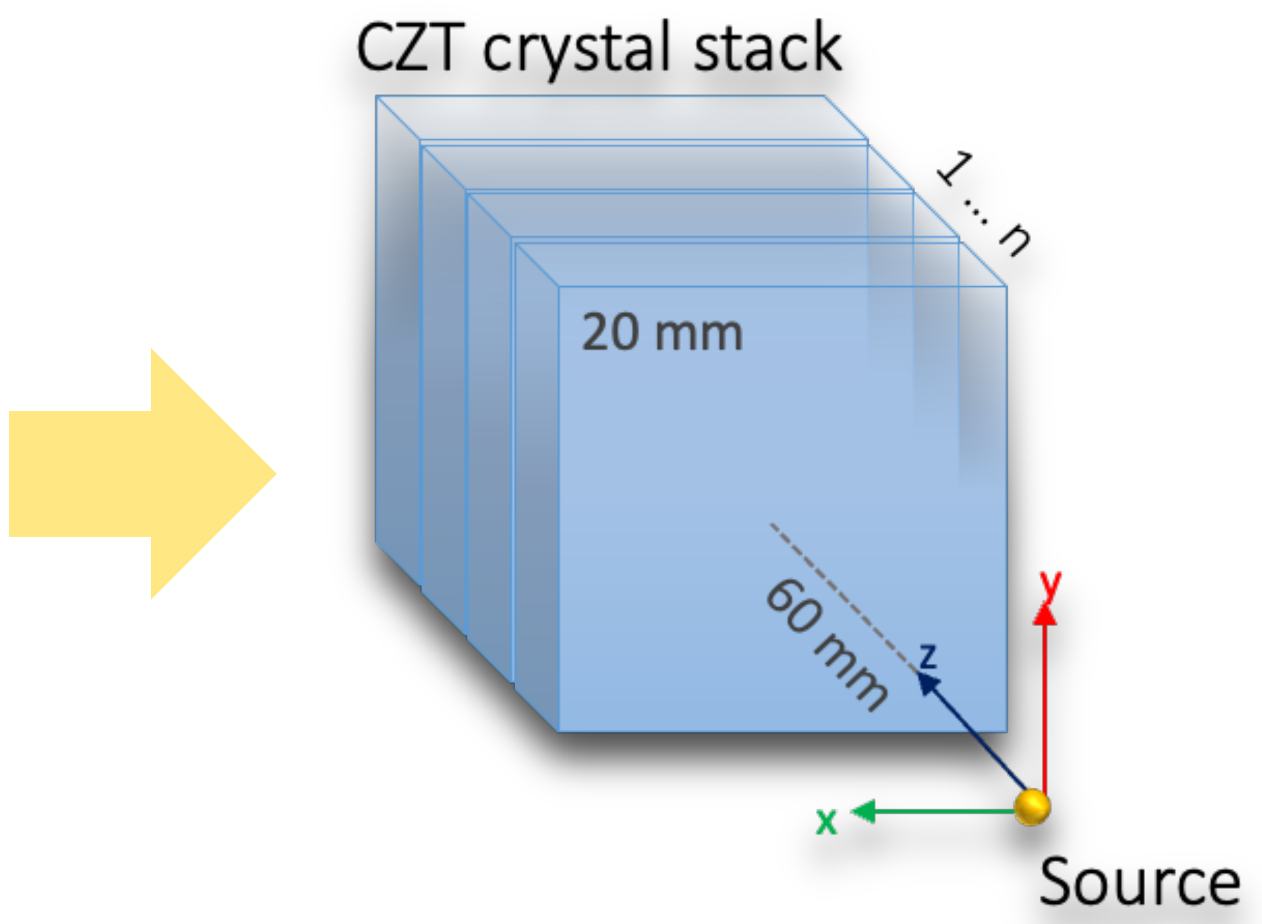
- Tomography FOV: cube 120 mm side centered with source and covering the entire phantom.



Detector simulated inspired in **CZT sensor by Due2Lab**

- Room-temperature gamma-ray spectroscopic
- Sub-millimetre spatial resolution and excellent energy resolution (around 1% FWHM at 661.7 keV)





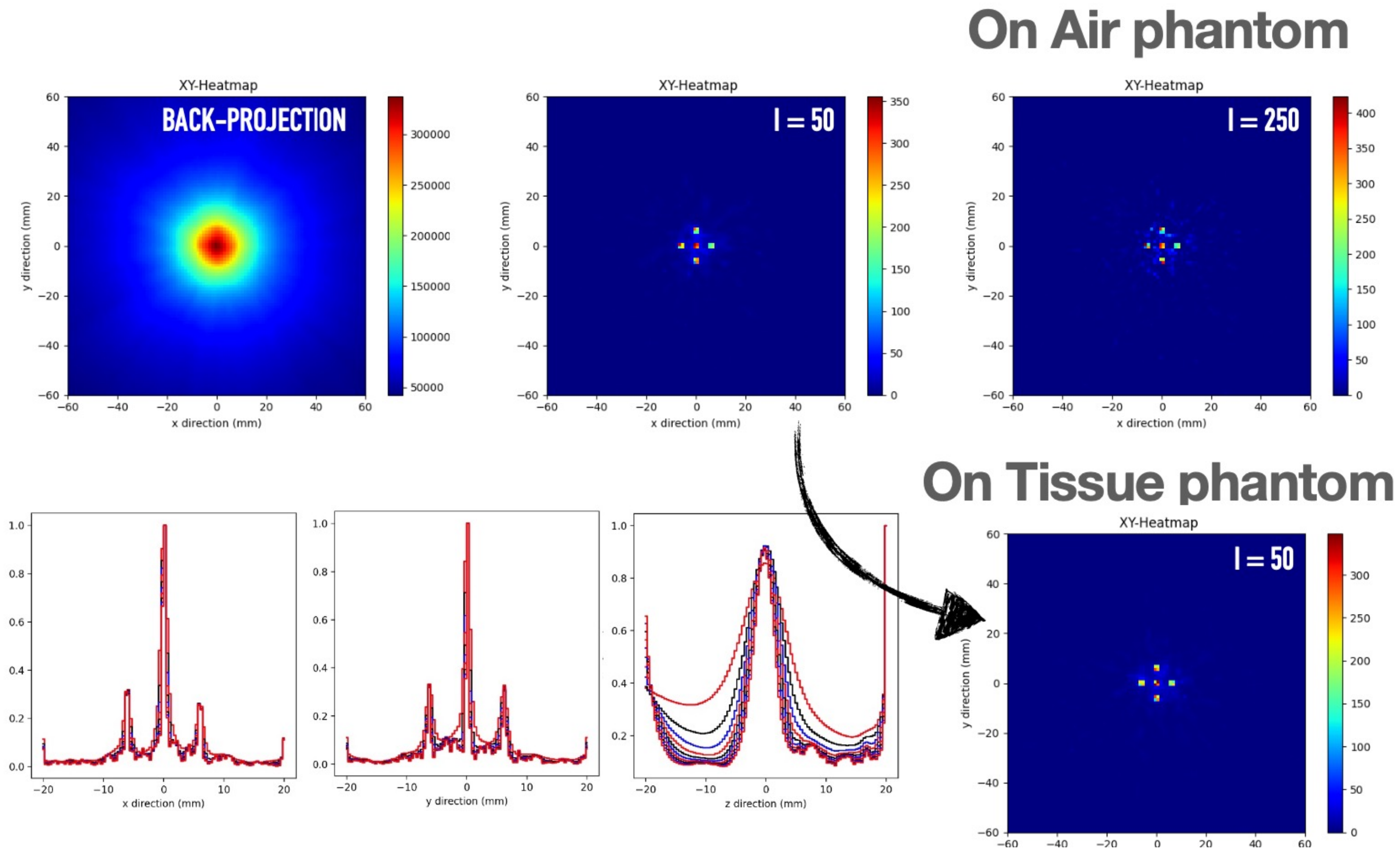
Abbene, L.; Principato, F.; Buttacavoli, A. and et al.: Potentialities of High-Resolution 3-D CZT Drift Strip Detectors for Prompt Gamma-Ray Measurements in BNCT. Sensors, 22, 1502 (2022)

MLEM reconstruction method validation

Maximum Likelihood Expectation Maximisation (MLEM) → Iterative method to reconstruct the most probable source distribution

$$\lambda_j^n = \frac{\lambda_j^{n-1}}{s_j} \sum_{i=1}^{N} \frac{t_{ij}}{\sum_k t_{ik} \lambda_k^{n-1}}$$

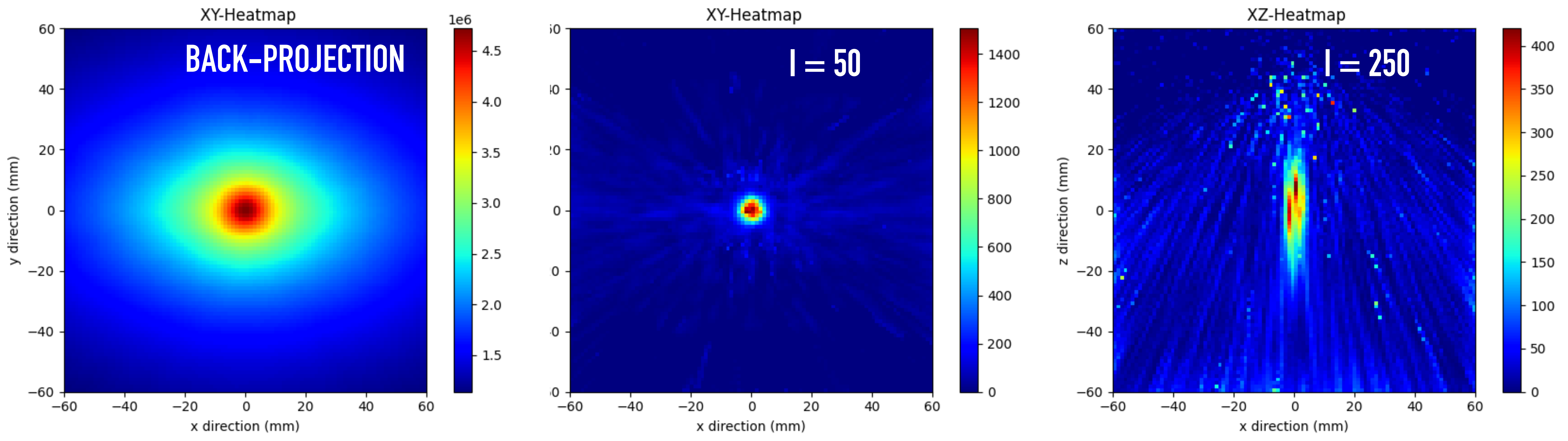
- λ^n_j = calculated amplitude of pixel *j* at the nth iteration
- s_j = sensitivity, i.e. the probability that a gamma ray originating from pixel *j* is detected anywhere
- t_{ij} = imaging response matrix, i.e. the transition probabilities generated by the measured events(first estimation: based on back-projection, λ_0)



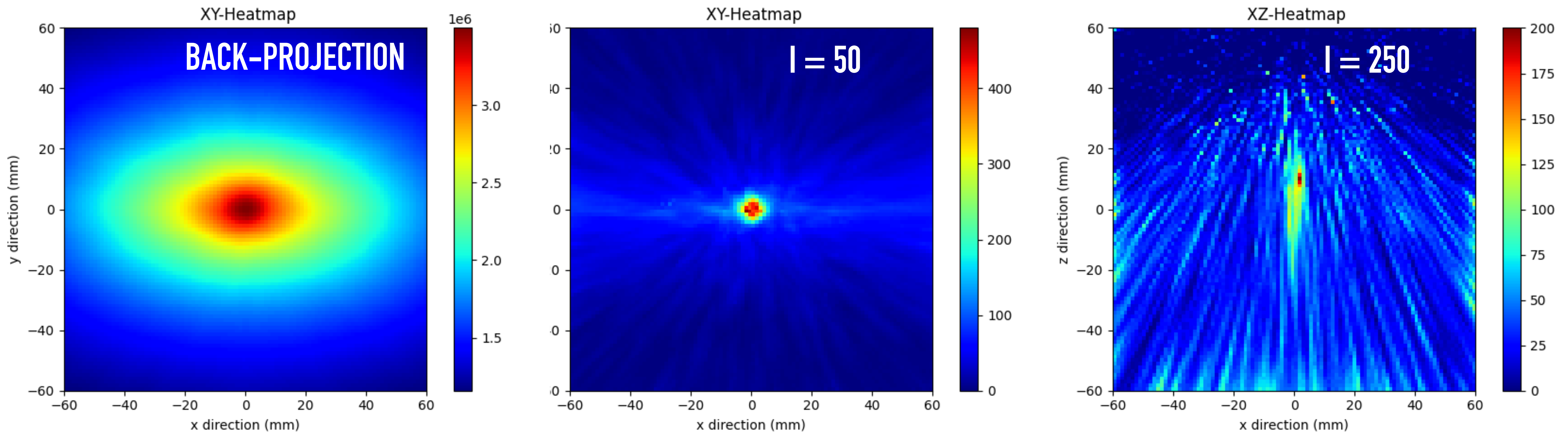
- Good resolution in x and y profiles, slightly worse in z direction (stretching effect)
- No image interference when phantom is added

Tumor-to-healthy 2D boron ratio study

On Tissue phantom, T/N = 5.0



On Tissue phantom, T/N = 2.0

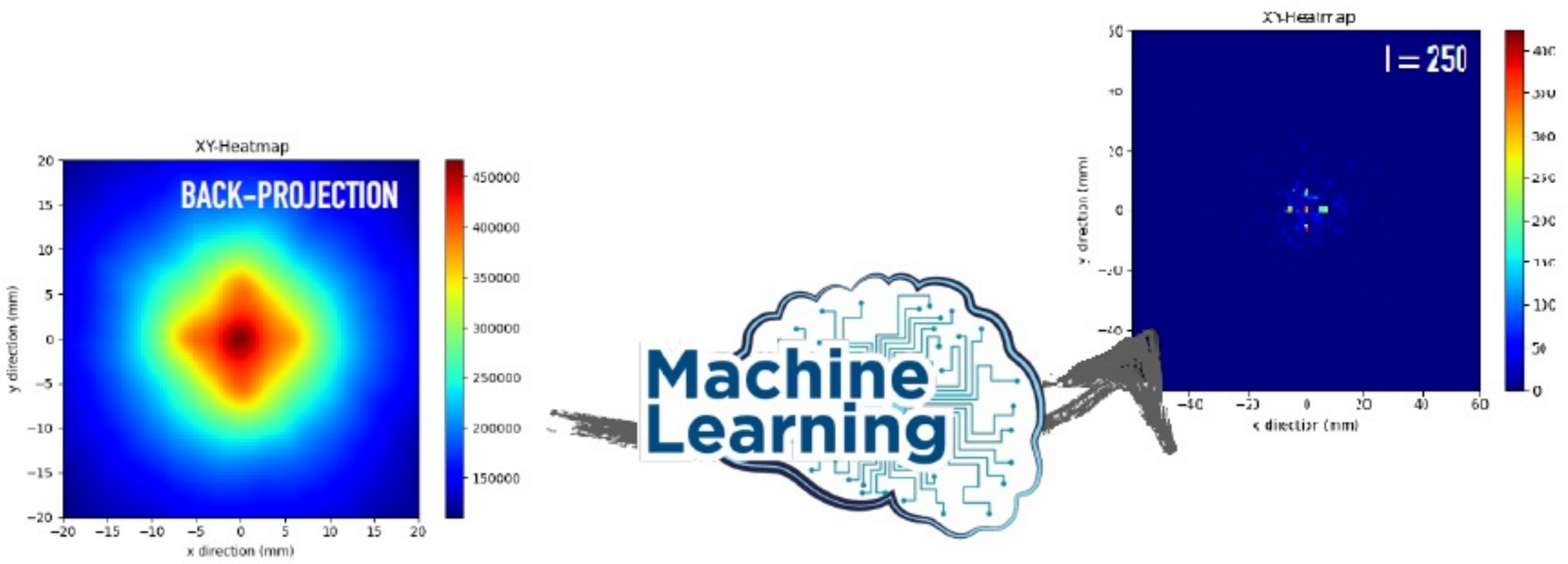


- Spheric source in more realistic conditions
- Two different ratios: **ideal case (T/N = 5)** and **(T/N = 2) extreme case** (clinical values are T/N>3)
- Both distributions resolute.

→ More iterations needed to solve the image in z (≈250)

Iteration methods and novel approach

- **Limitation for online dose measurements:** MLEM works only post-irradiation, tomography takes few mins (≈ 20 min)
- New approach **to go from the back-projection image to the tomography dose by using Deep Learning**



Training **Deep Learning** model with back-projection and tomography labels sets to make **tomography reconstruction**

No availability of Compton images databases within BNCT

First DL approach: tumor monitoring by segmentation using Transfer Learning

Tumor Monitoring DL model

- **Matlab pipe-line** for segmentation of images
- Use of Convolutional Neural Network model with a **Residual U-net Architecture (ResNet)**, widely used for segmentation

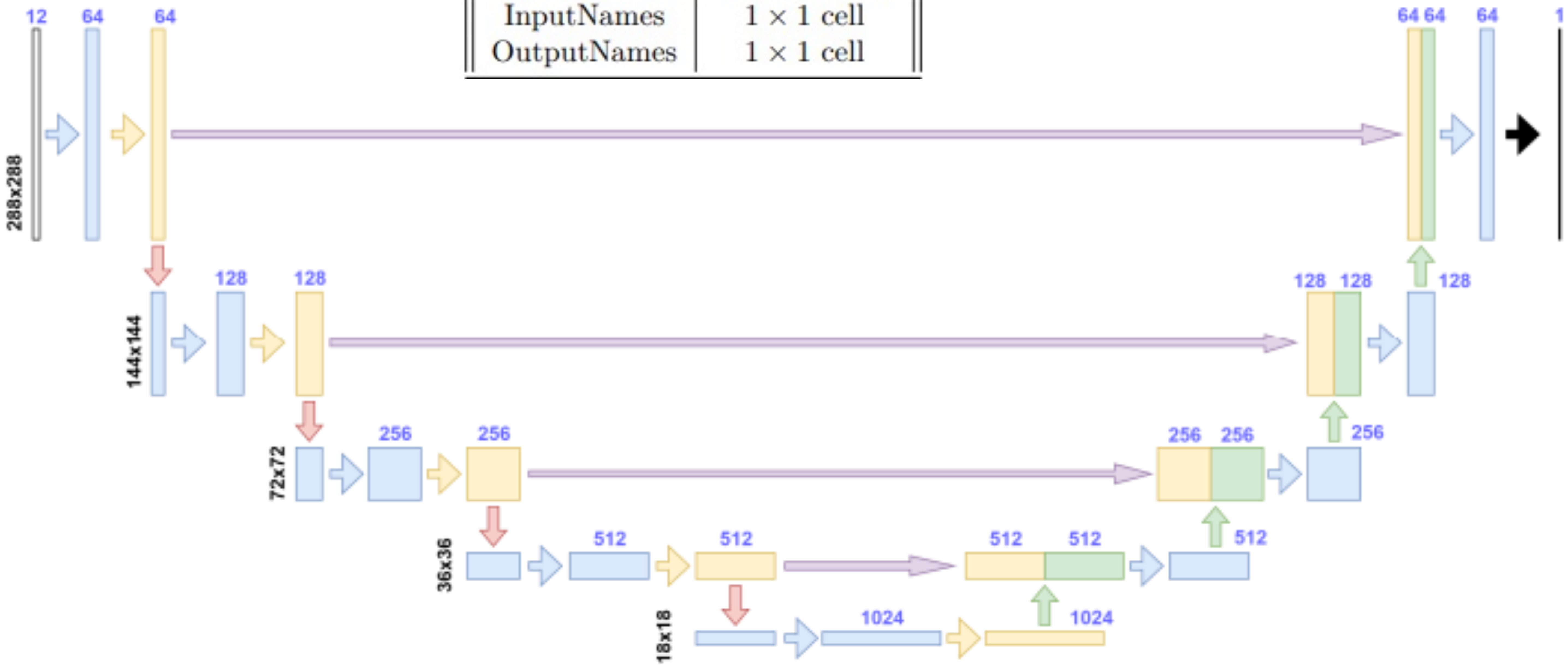
Test metrics: **accuracy and sensitivity**

$$Accuracy = \frac{TP}{TP + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

Resnet U-net architecture

Property	Value
Layers	206 × 1 Layer
Connections	227 × 2 table
InputNames	1 × 1 cell
OutputNames	1 × 1 cell

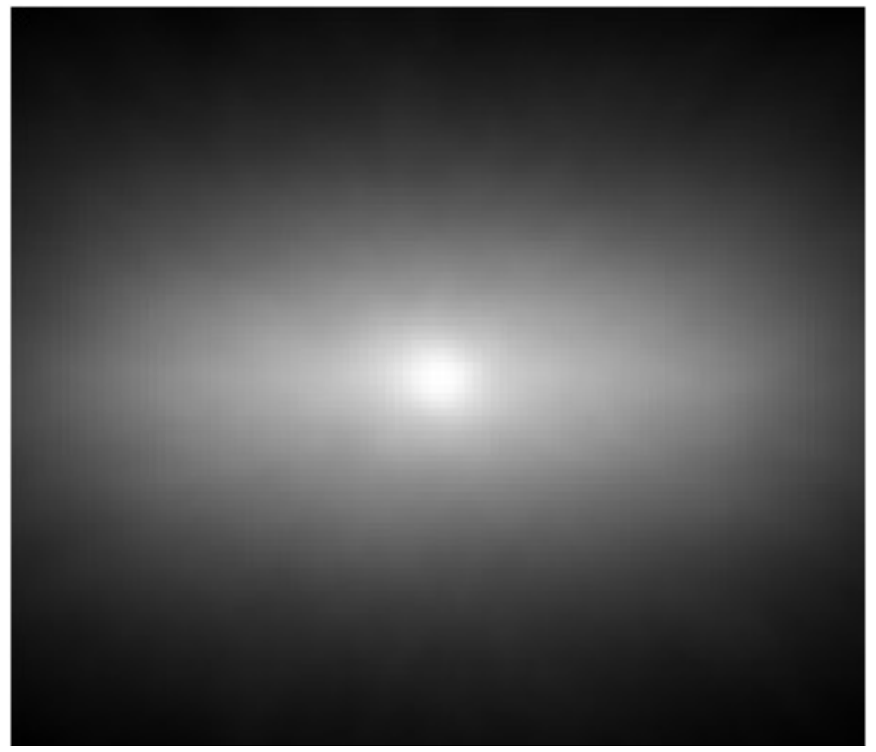
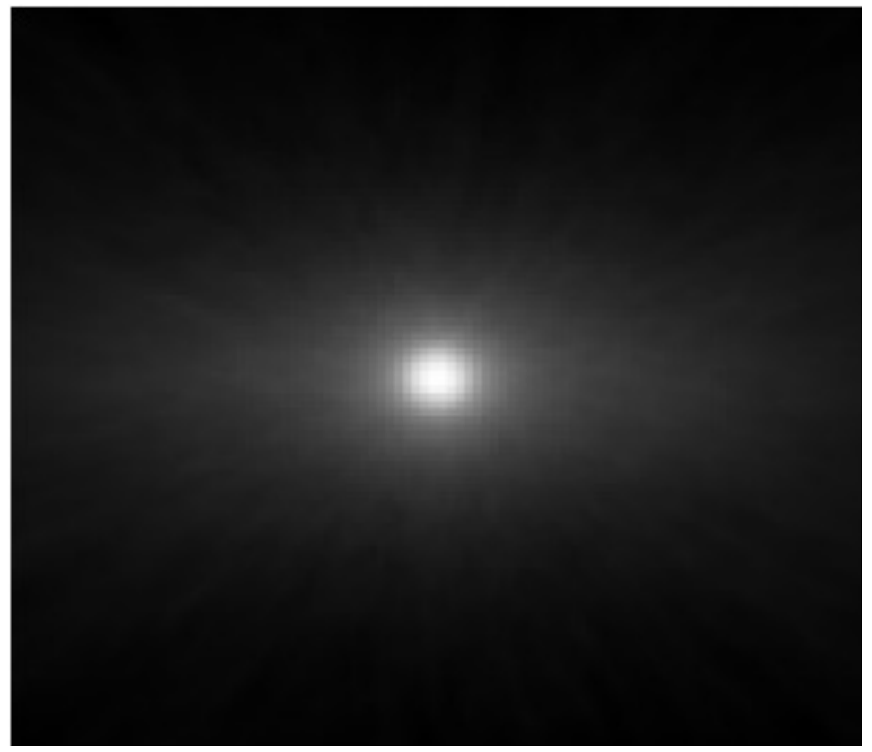
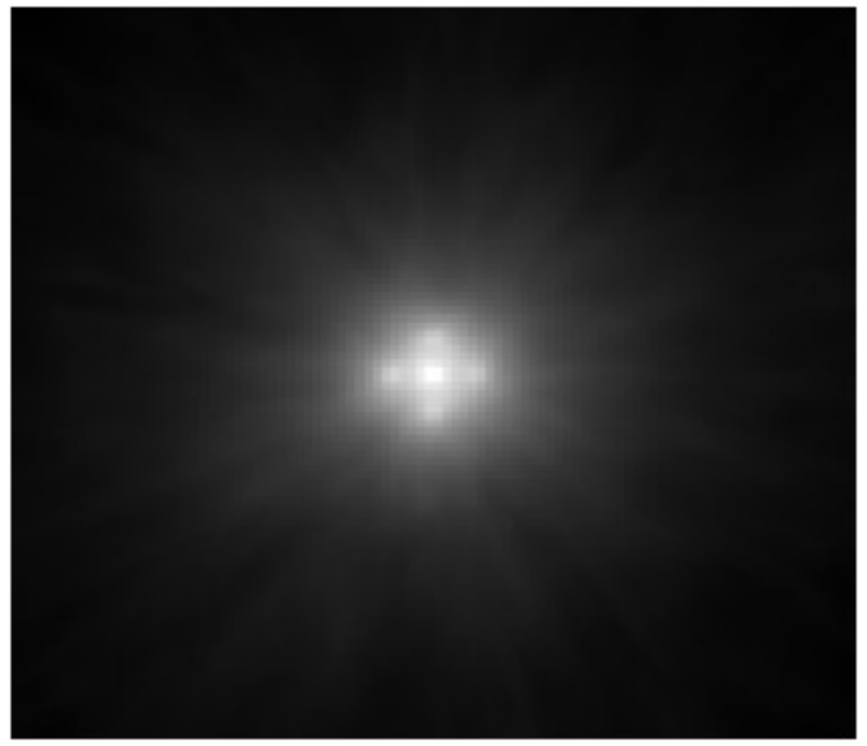


(a)

Model performance performance

	Accuracy	Sensitivity
case 1	79.56%	99.87%
case 2	4.83%	100%
case 3	19.68%	100%
case 4	3.81%	100%

Normalized back projections

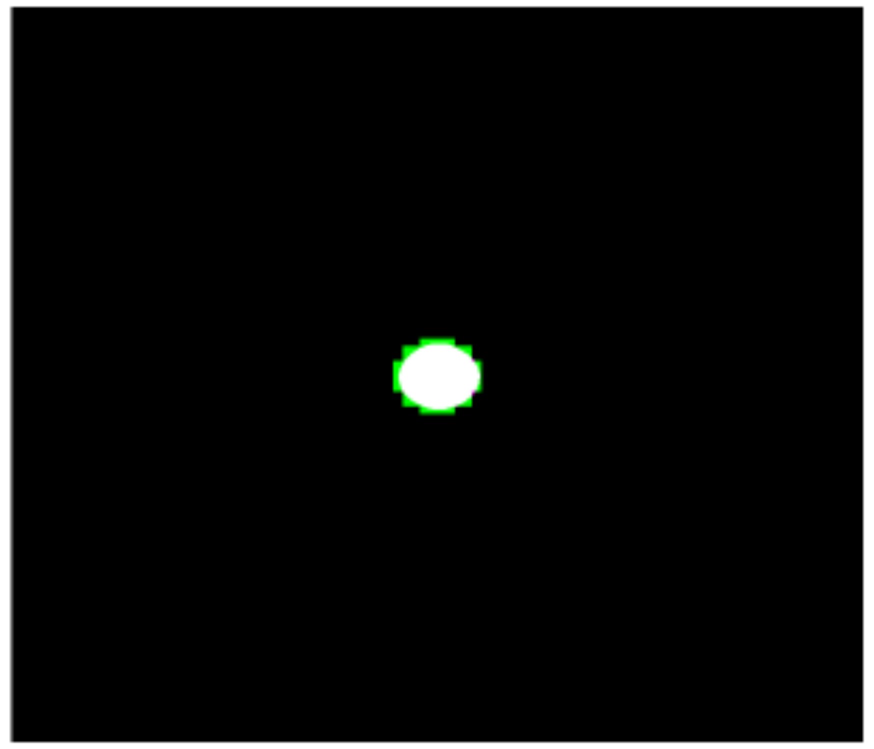
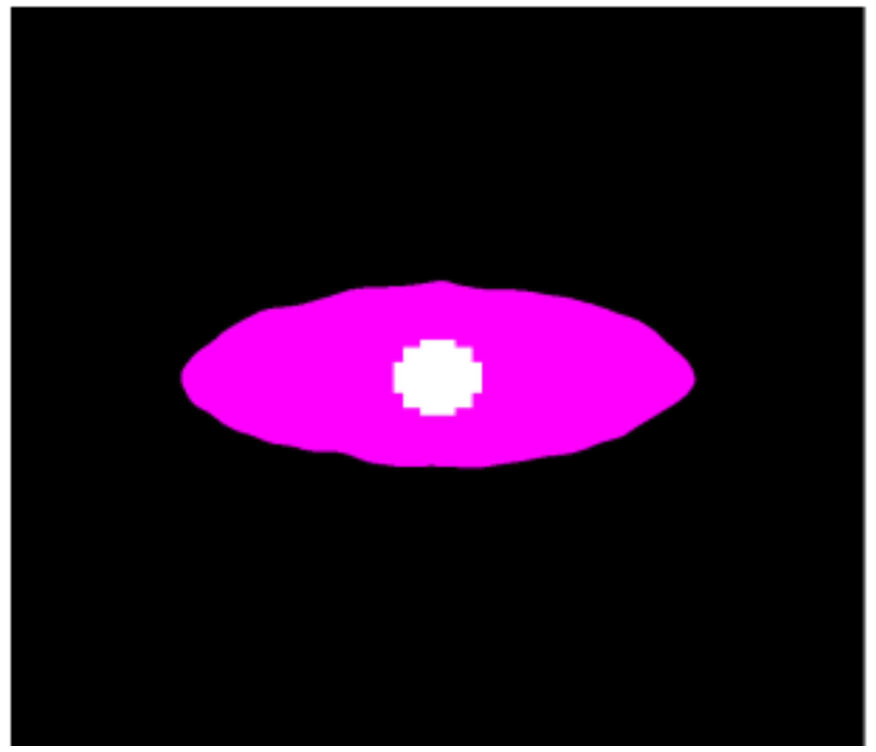
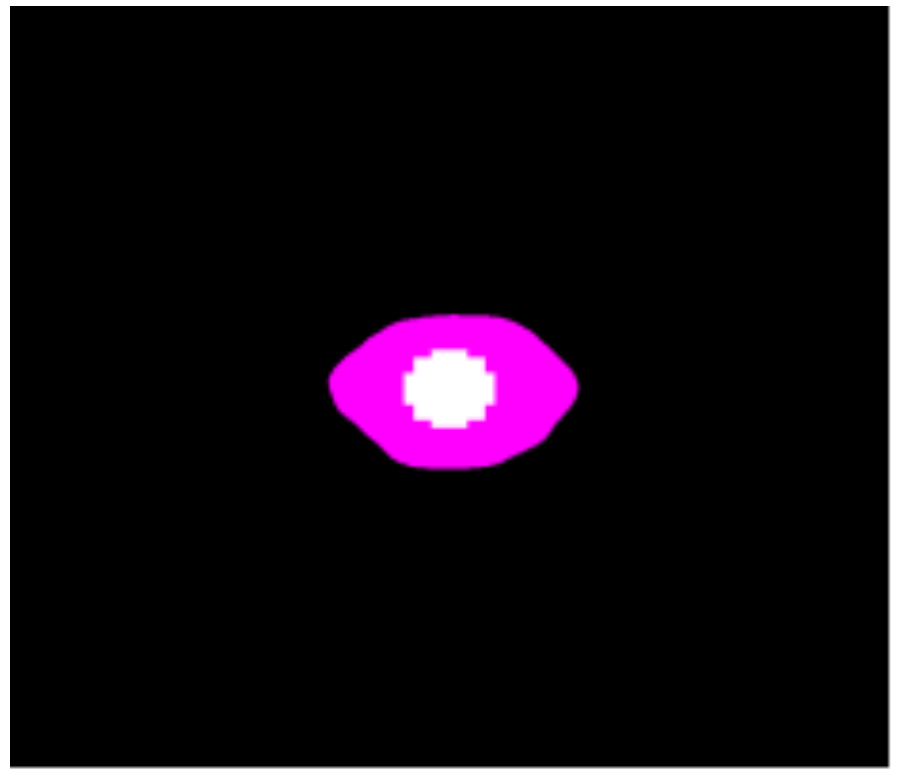
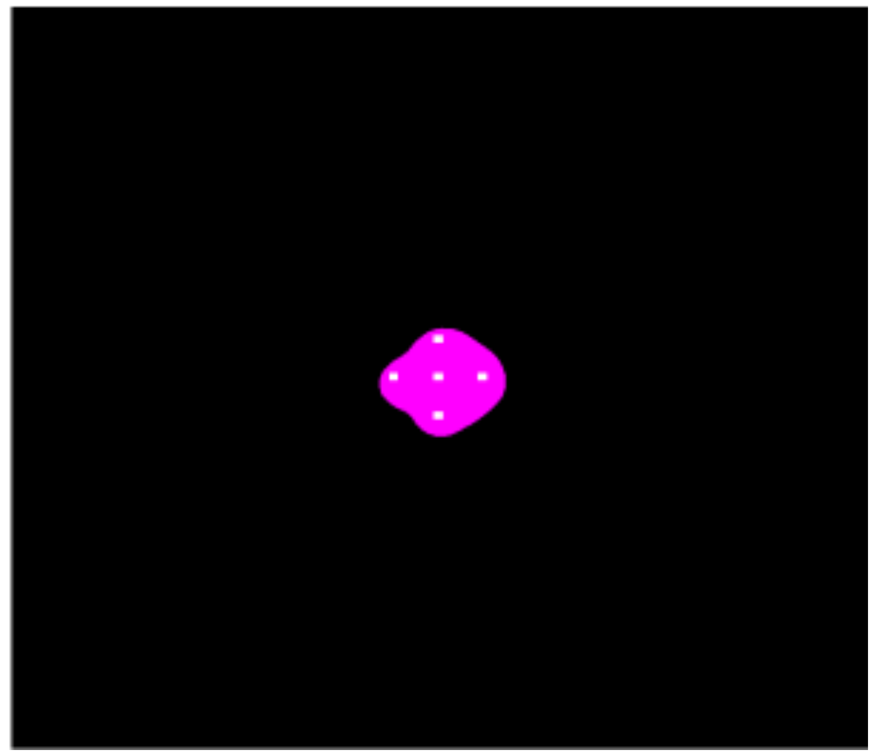
Case 1: Spheric source in Air

Case 2: Spheric source in Tissue (T/N=2)

Case 3 Spheric source in Tissue (T/N=5)

Case 4: 5 point-like source in air

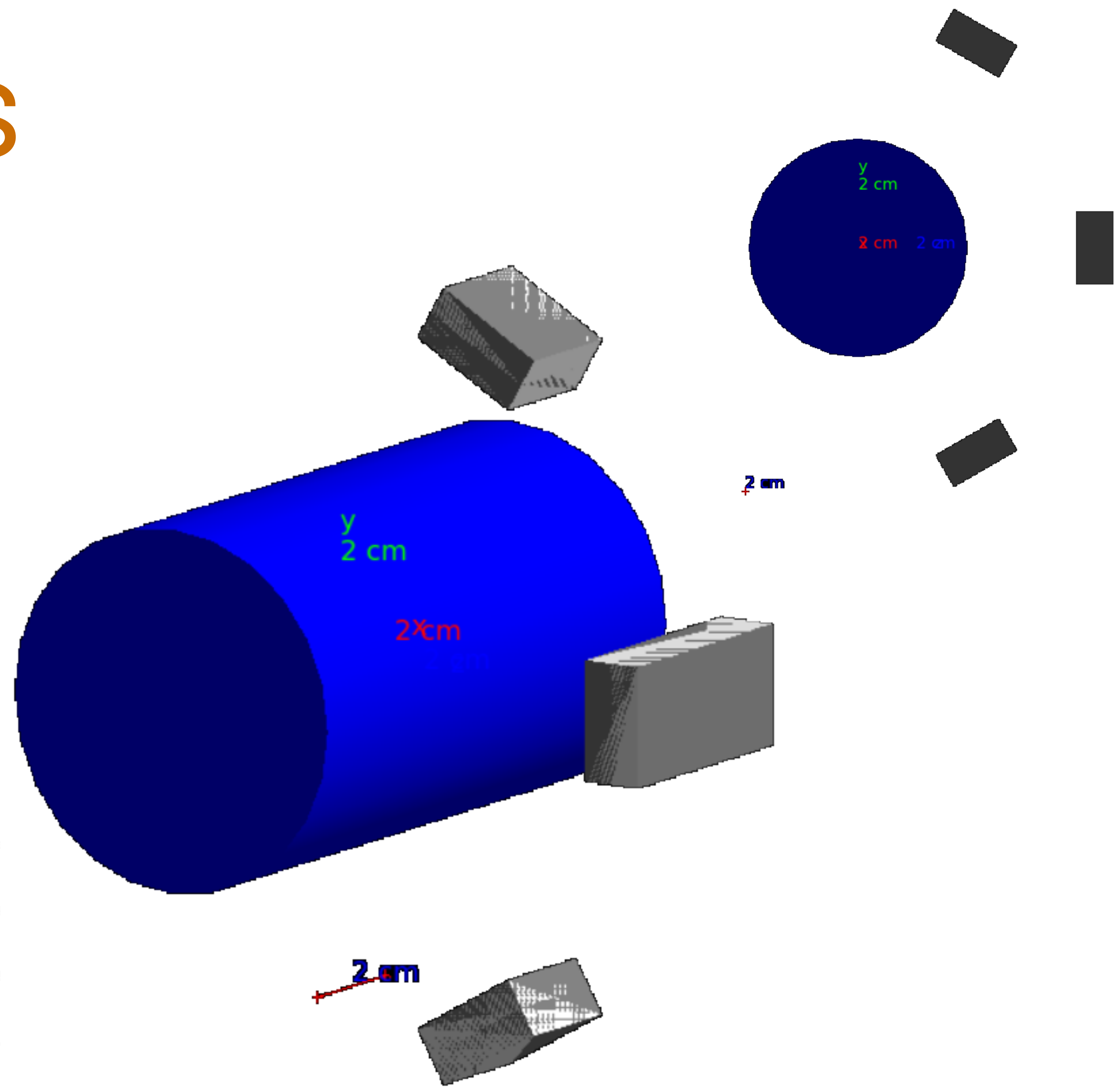
ResNet segmentation

New geometry and simulations

New geometrie to reduce z-stretching and **increase distribution database** (DB) → improve 3D reconstruction and DL performance

- 4 four-layers detectors geometry (2 frontal, 2 at ±60°); this was the one used for deep learning image reconstruction in this study



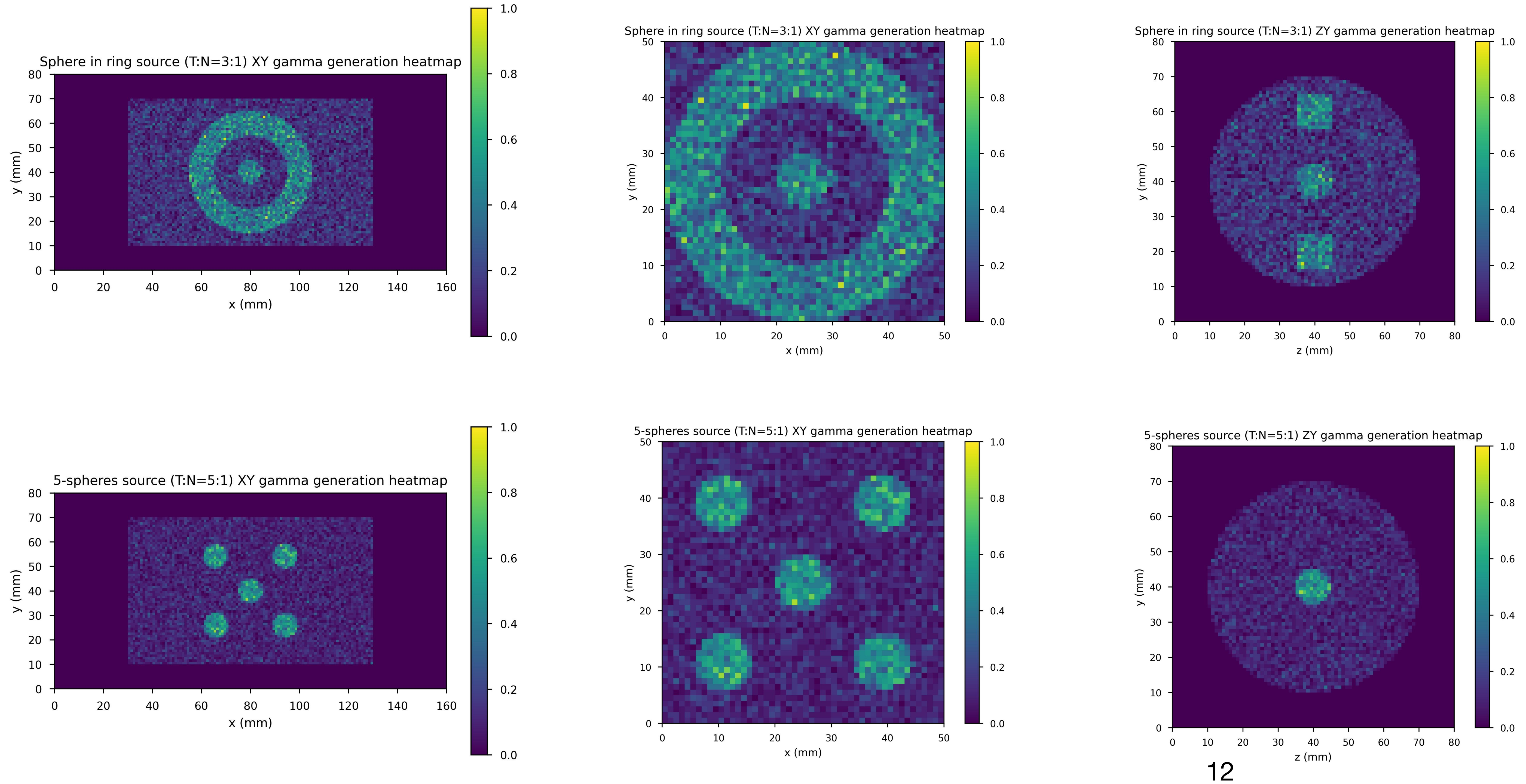


Image DB with new source distributions
\+ noise introduction
\+ rotation transformation

U-Net model variants

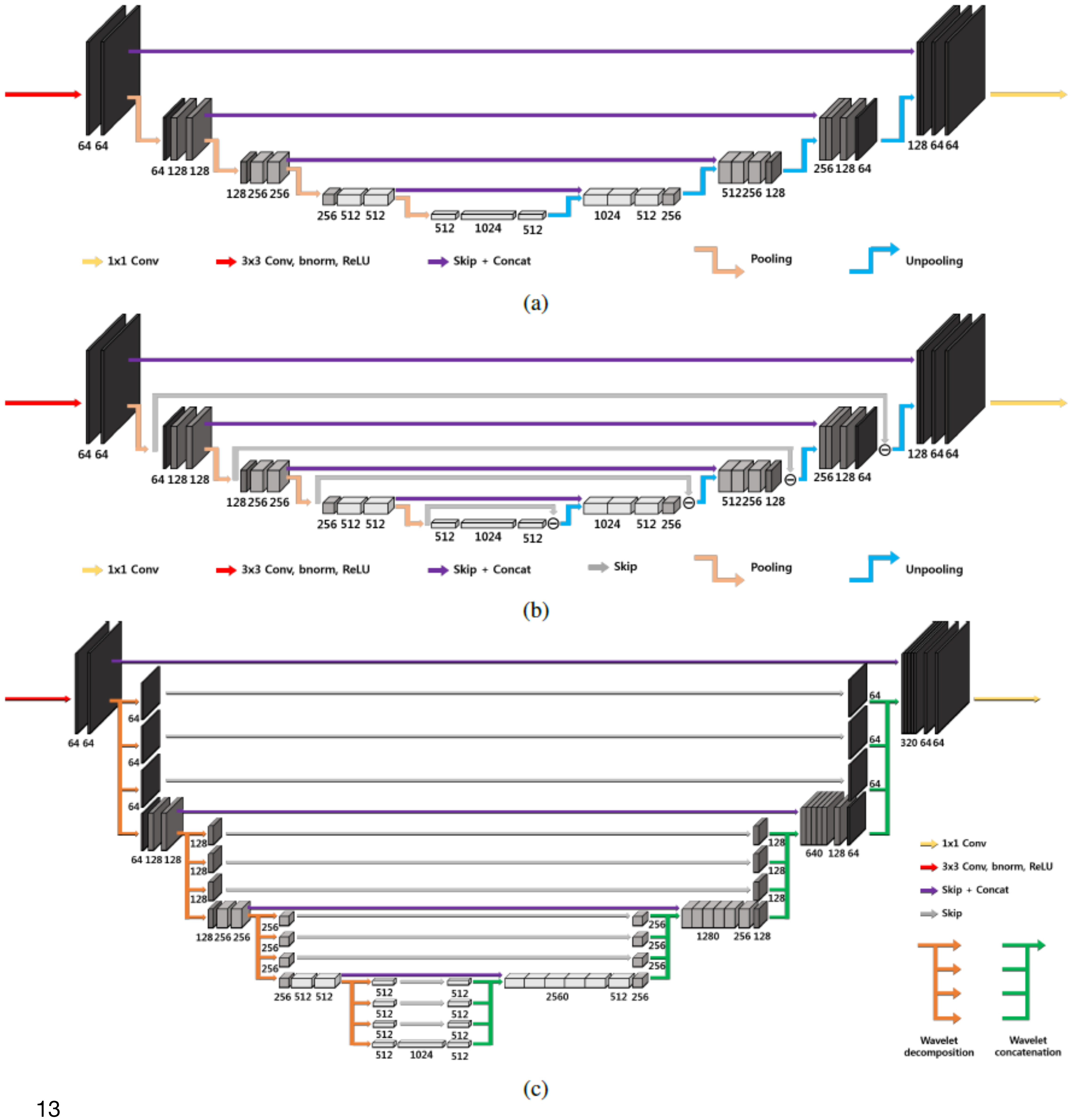
- U-Net and improved versions used for image denoising*:

  (a) classical U-Net

  (b) dual frame U-Net

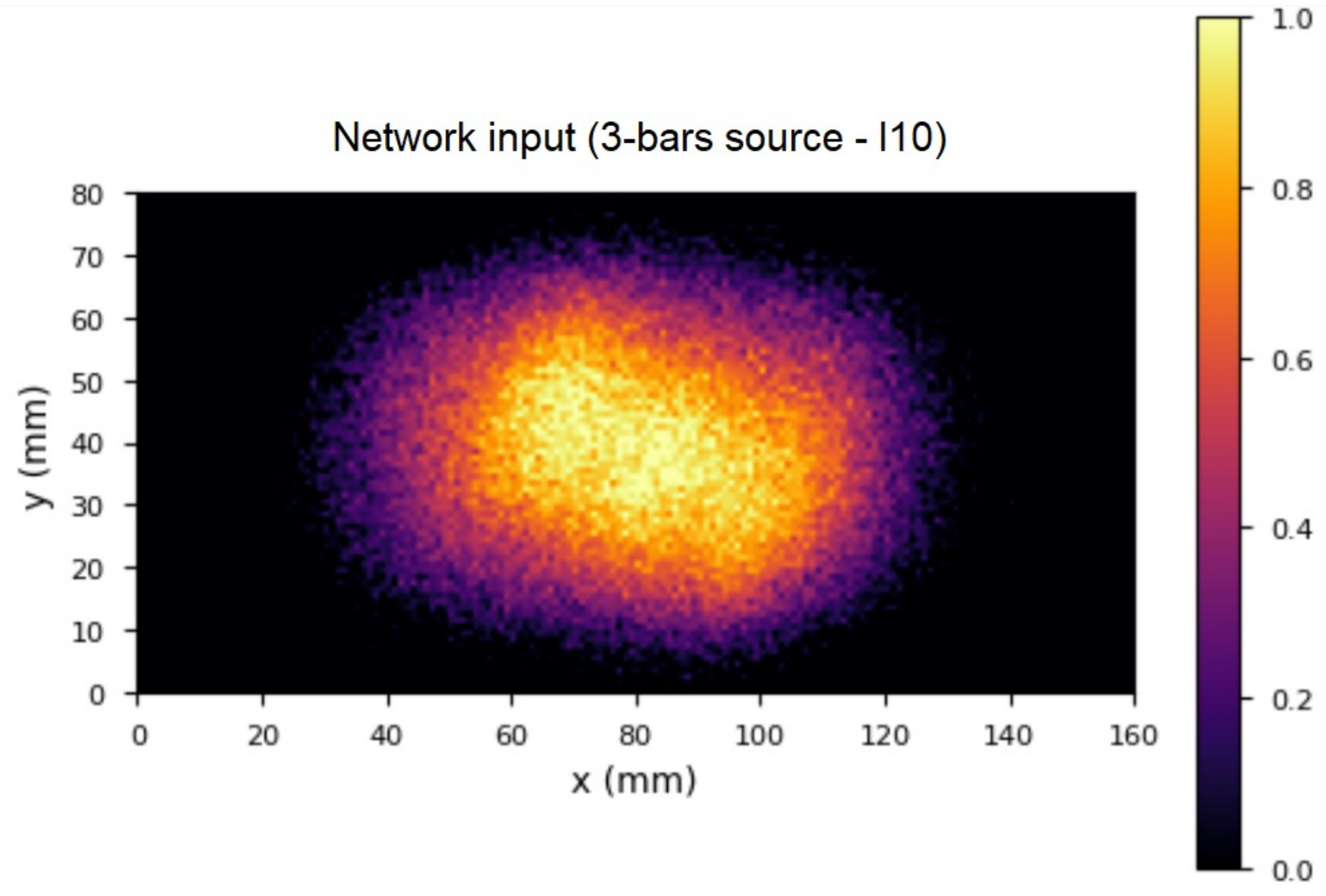
  (c) tight frame U-Net with Haar filter bank

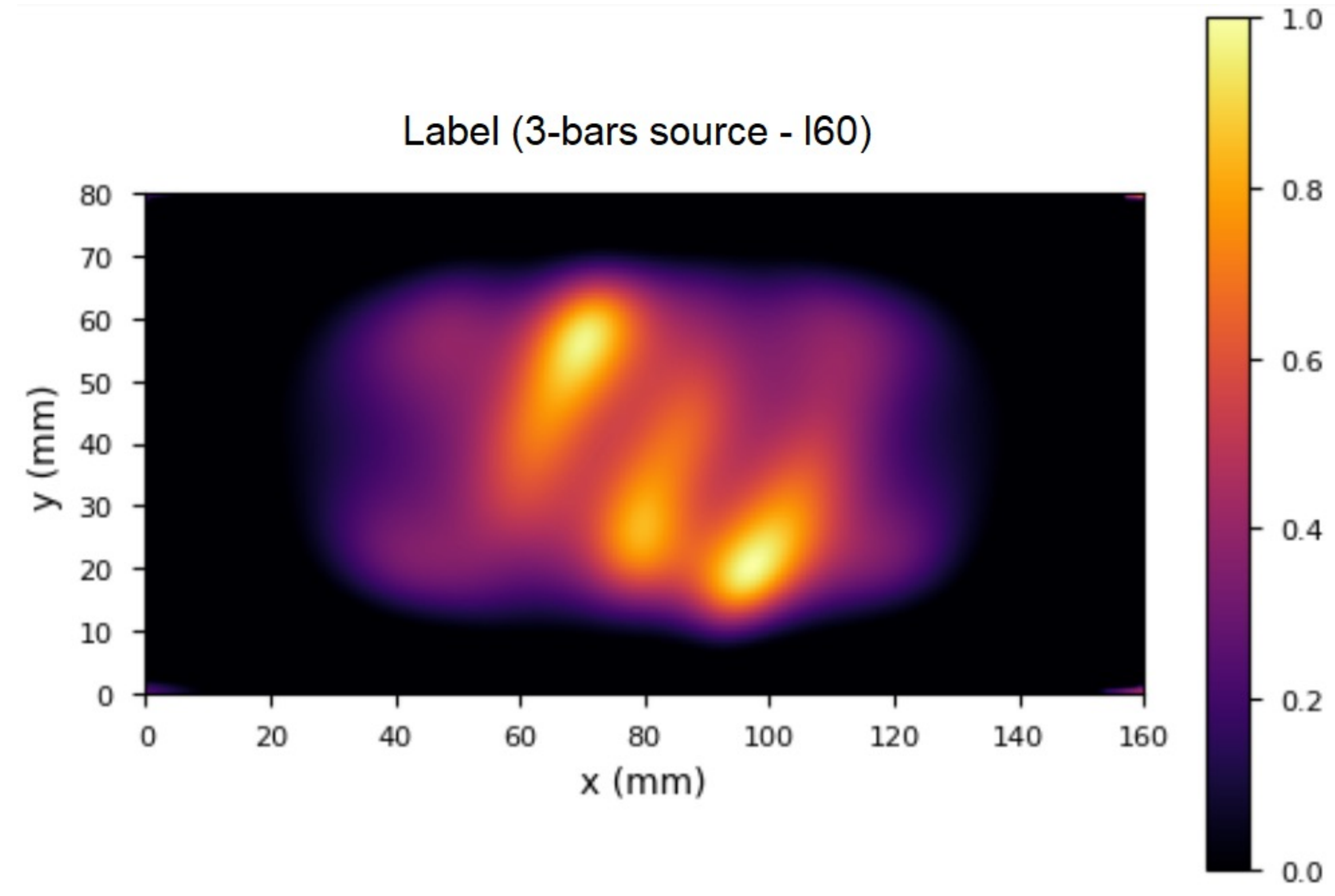
- The input images are the results of the tenth iteration (~ 4-6 min) of MLEM algorithm
- The models were impletented in 3-D variants

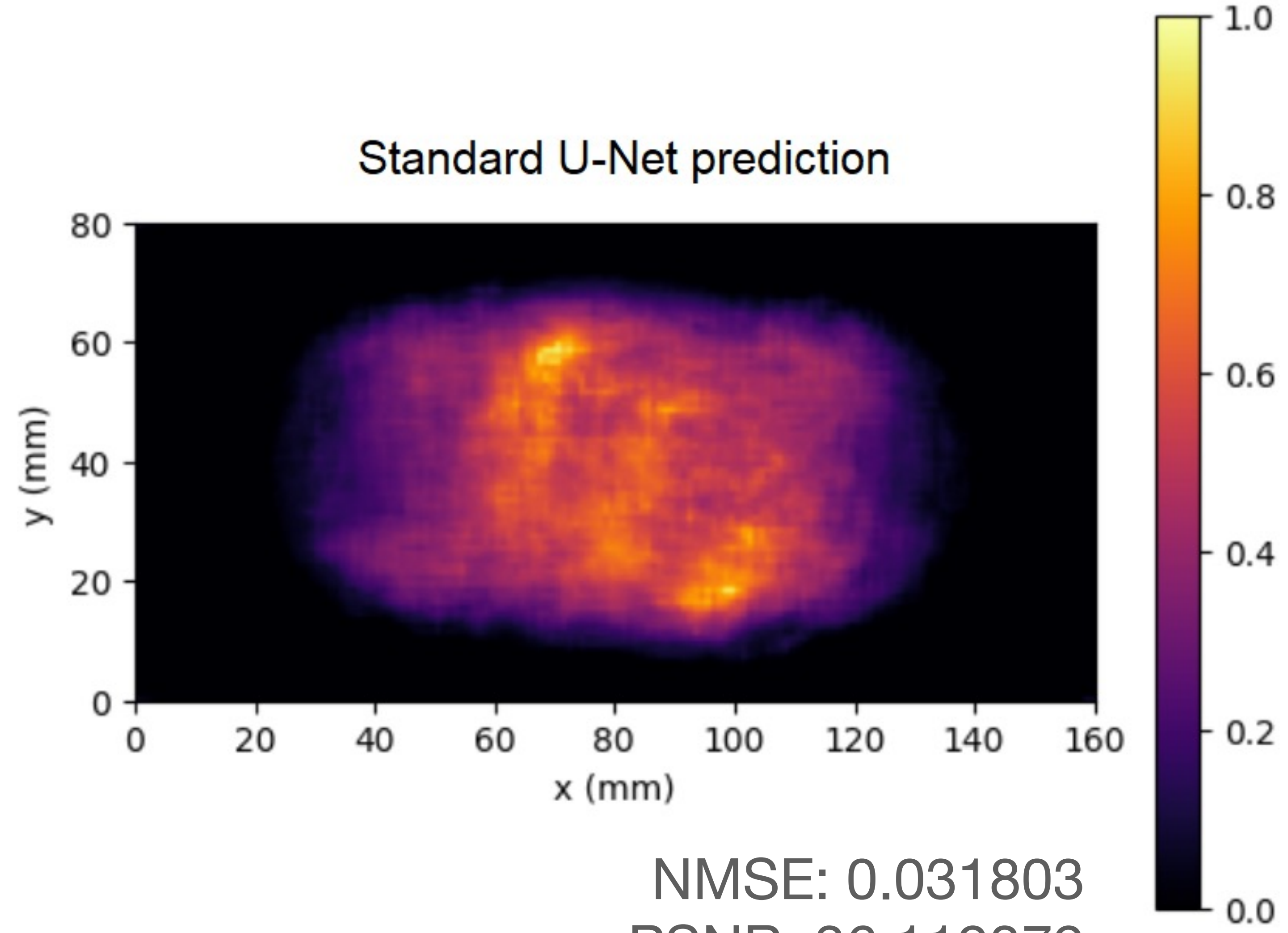


*Framing U-Net via Deep Convolutional Framelets: Application to Sparse-view CT
Yoseob Han and Jong Chul Ye, Senior Member, IEEE

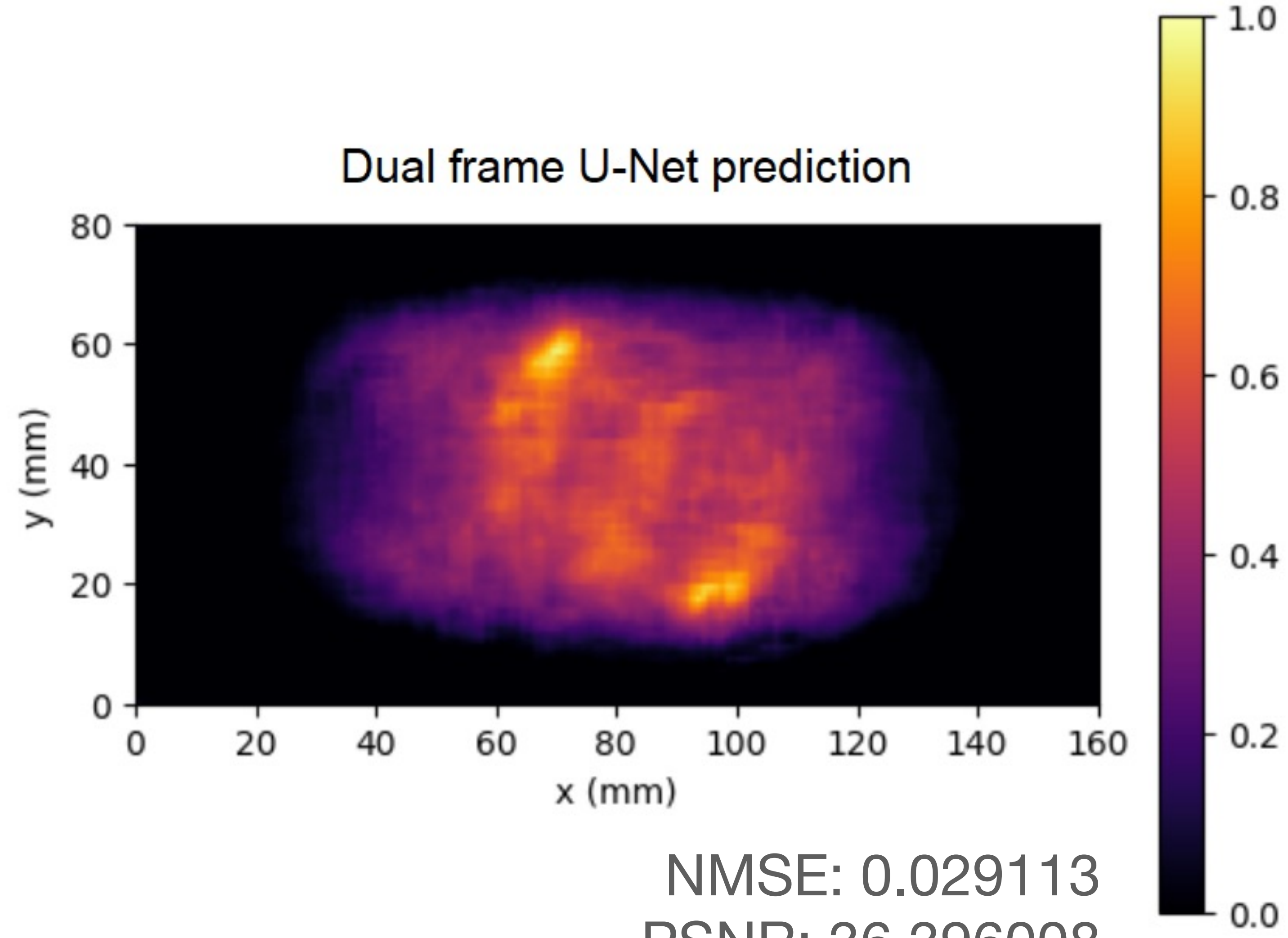
Example of U-Nets predictions



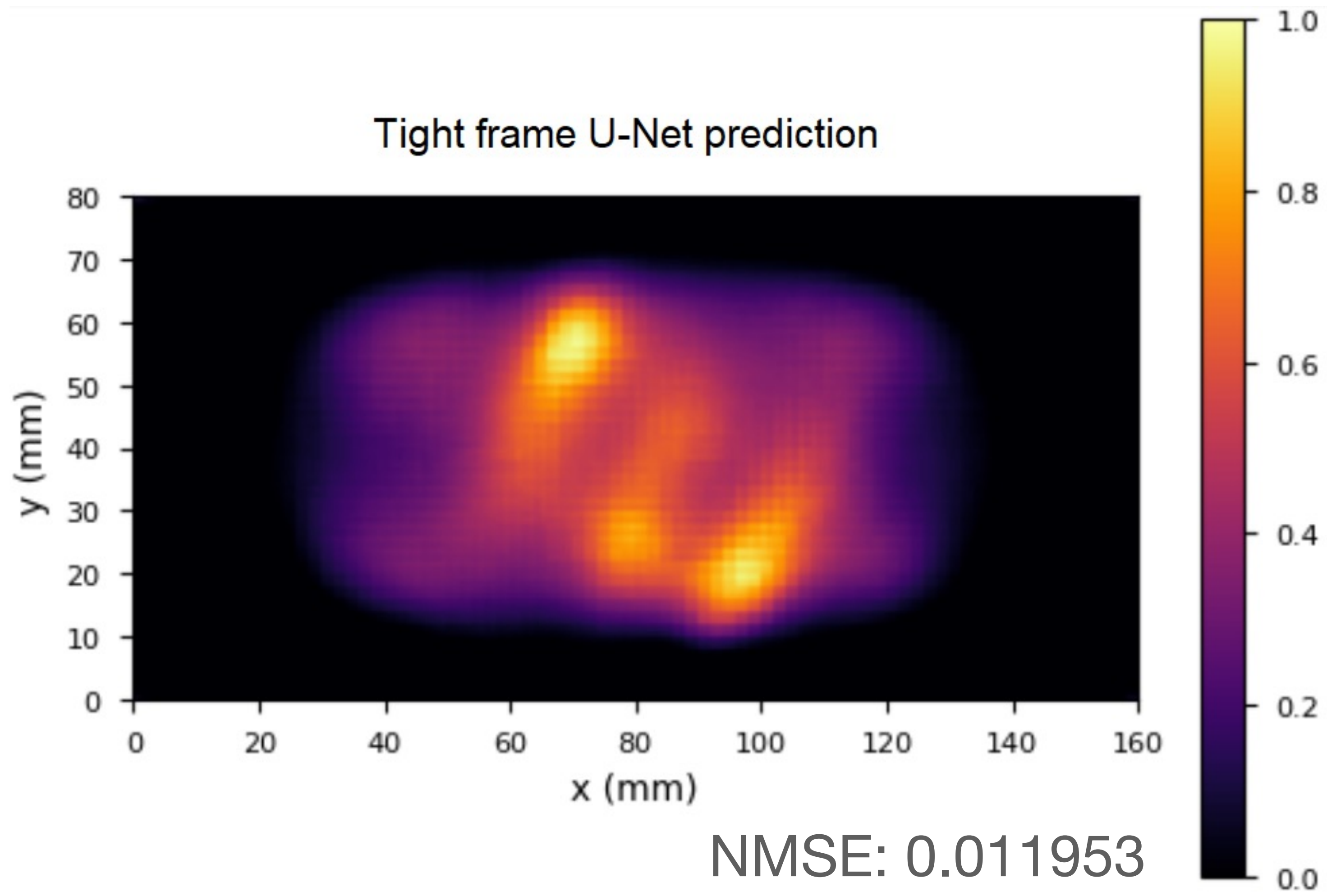




NMSE: 0.031803
PSNR: 36.119379
SSIM_3D: 0.754417



NMSE: 0.029113
PSNR: 36.396008
SSIM_3D: 0.7262286



NMSE: 0.011953
PSNR: 40.615813
SSIM_3D: 0.853548

Conclusions

- It was proved the Compton camera imaging approach for dose tomography within Boron Neutron Capture Therapy
- By using an iterative method (MLEM) it was possible the dose reconstruction but not applicable in in-vivo therapy situations
- Deep Learning was used as first approach for tumor monitoring with good accuracy/sensitivity compromise
- By augmenting the image data-base with simulated data, few models based on 3D U-net were training and their performances seems to be promising (ongoing)

What's next?

- Implementation of hybrid methods and study their performances
- Working on detector development for tests with experimental data

Thanks!

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