Deep learning for dose reconstruction in BNCT with Compton camera detector

MASTER THESIS UPDATES

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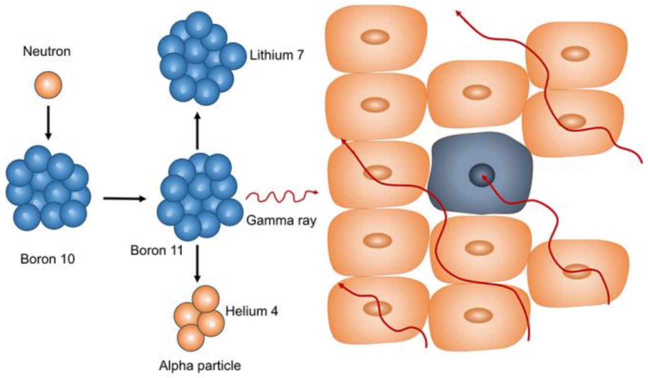
BNCT and Compton camera detector



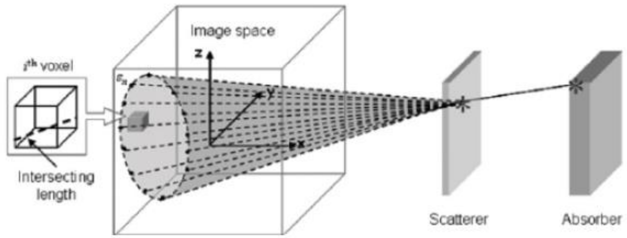
Capture reaction: $^{10}B(n,\alpha)^{7}Li$

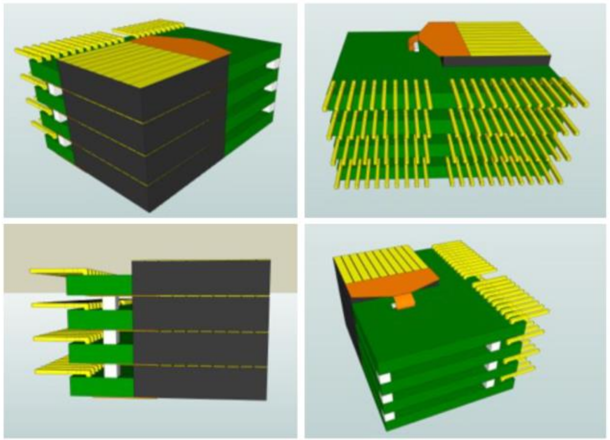
$$^{10}B + n \rightarrow {}^{7}Li + \alpha + 2.79\ \text{MeV} \quad (6.1\%)$$

$$\rightarrow {}^{7}Li^{*} + \alpha + 2.31\ \text{MeV} \quad (93.9\%)$$

$$^{7}Li^{*} \rightarrow {}^{7}Li + \gamma + 0.478\ \text{MeV}$$

$\sigma = 3837$ b





BNCT is an innovative hadron therapy at cell level with high selectivity for cancer tissue based on the neutron capture reaction 10B(n,α)7Li.

Compton imaging can be applied for dose estimation.

3D CZT drift strip detector realized by Pavia University.

Maximum Likelihood Expectation Maximization (MLEM)

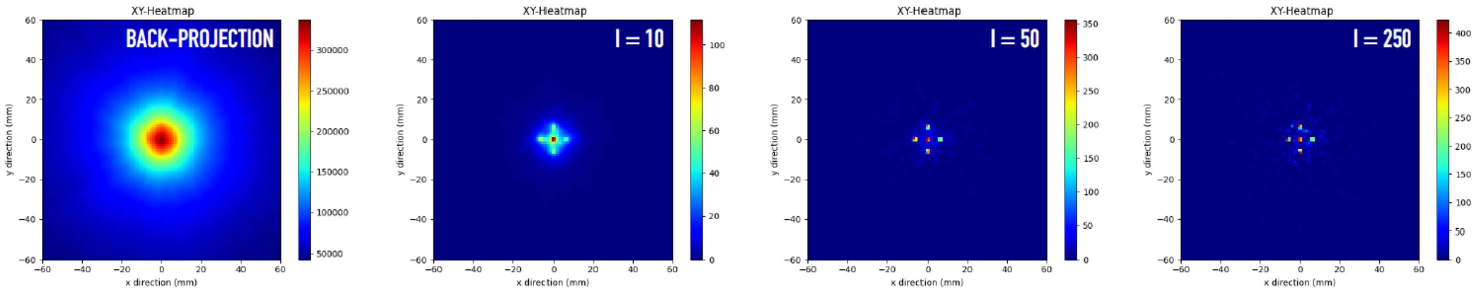
Iterative method to produce the most probable source distribution.

Computationally expensive!

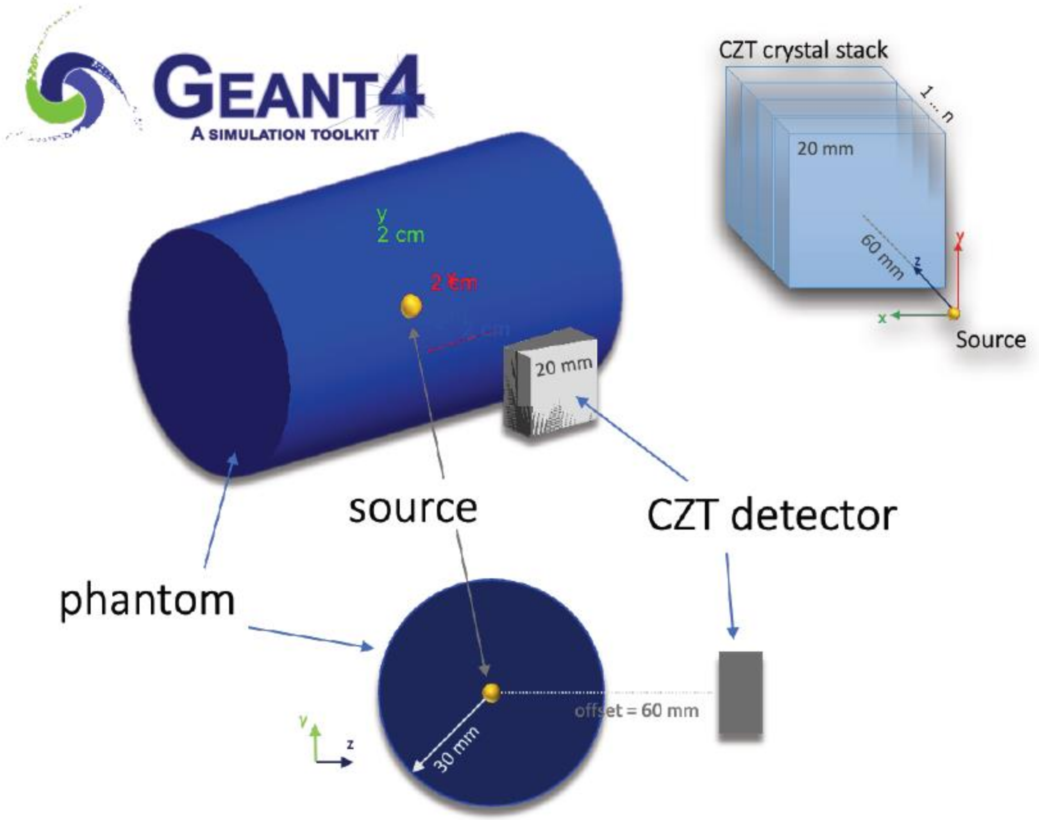
This study pursues the avoidance of the iteration time by using deep learning techniques, providing a prompt dose reconstruction during the treatment.

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

$\lambda^n{}_j$ = 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
s_{ij} = imaging response matrix, i.e. the transition probabilities generated by the measured events
(first estimation: based on back-projection, λ_0)



Monte Carlo simulation



Pre-existing Monte Carlo simulation: Compton camera made of CZT detectors, gamma source, phantom material.

The simulation has been expanded, considering different source geometries, therapeutic ratios, detector geometries.

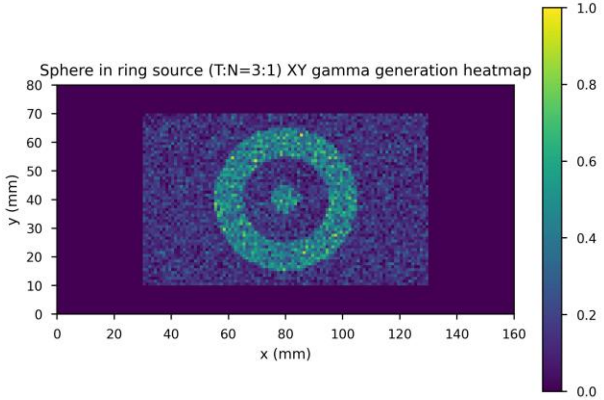
Revision of PrimaryGeneratorAction implementation: boron concentration

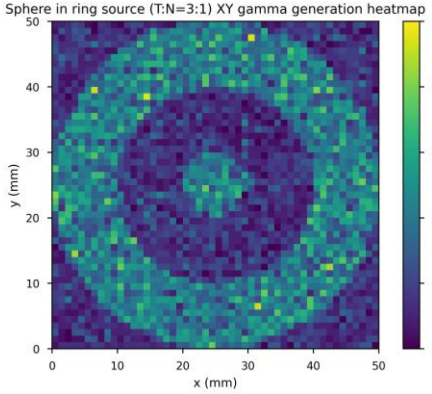
The generation of gamma inside the tumor region and inside the cylinder has been modified in order to obtain the correct therapeutic ratios ($C_T : C_N = 5{:}1, 4{:}1, 3{:}1$) according to the following probability ratio:

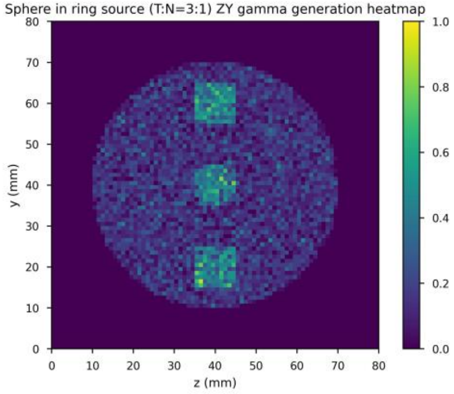
$$\frac{P_T}{P_C} = \frac{V_T}{V_C}\left(\frac{C_T}{C_N} - 1\right)$$

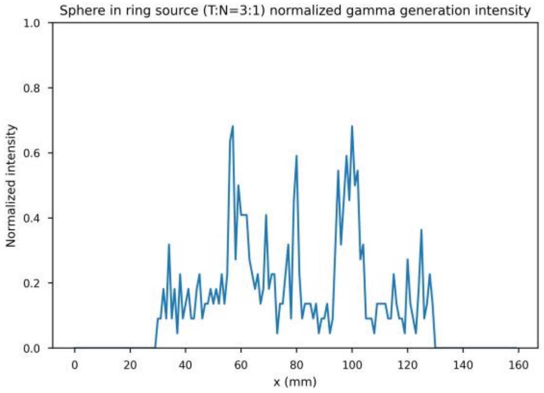
Where V_T is the tumor region volume and V_C is the cylinder volume.

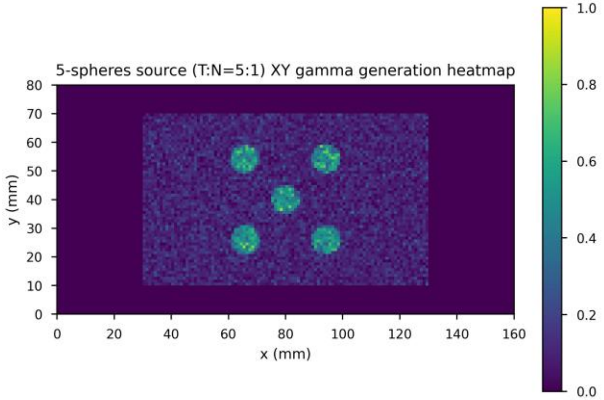
Some source geometries

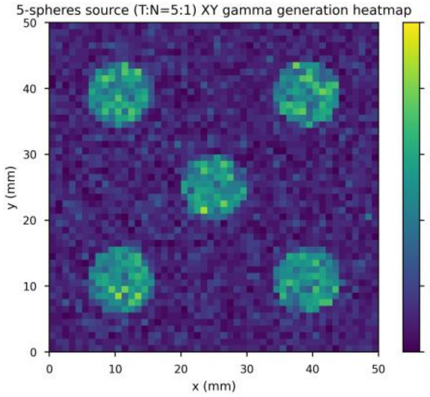


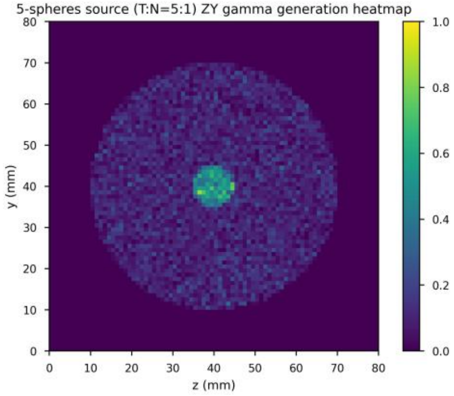


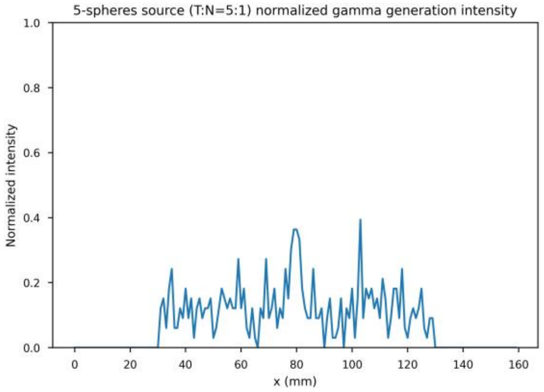




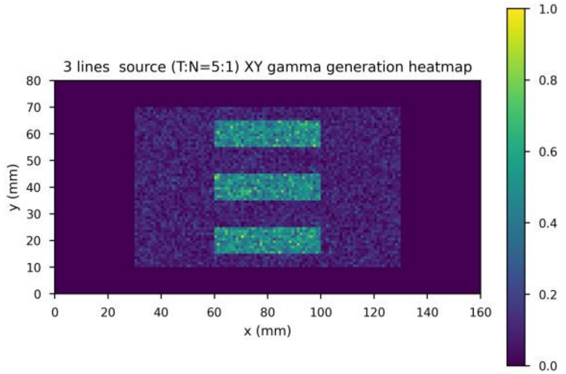


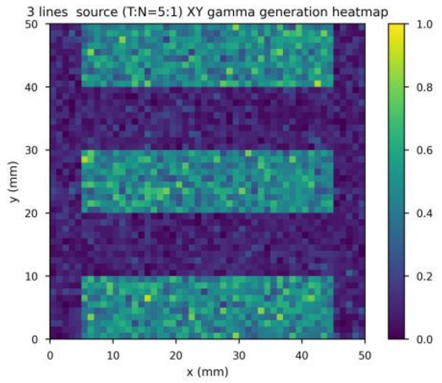


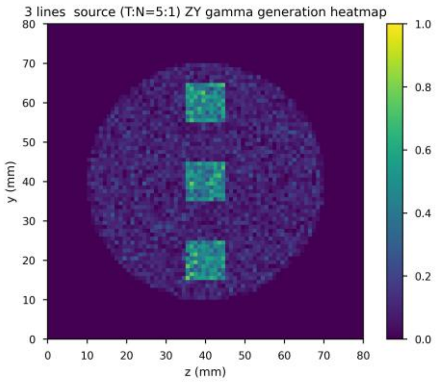


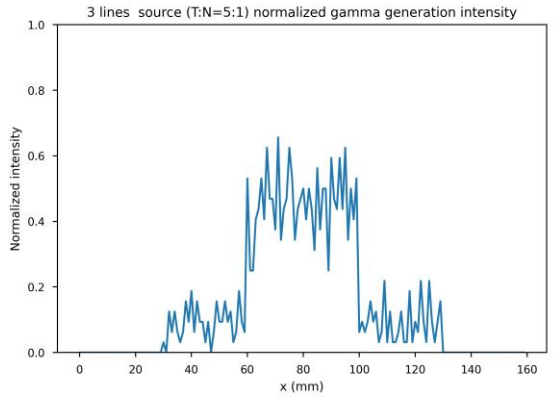


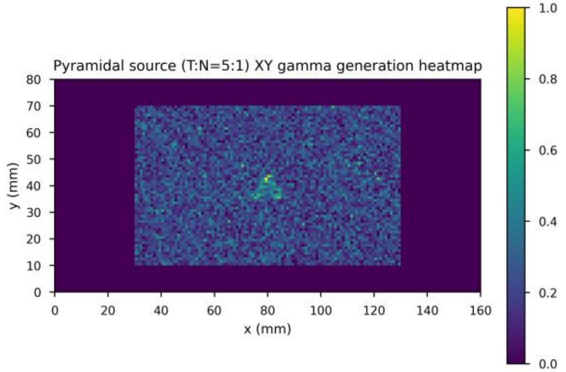
Some source geometries

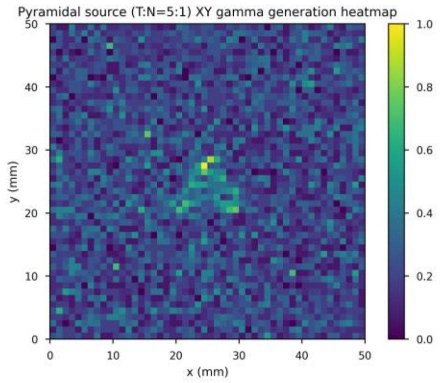


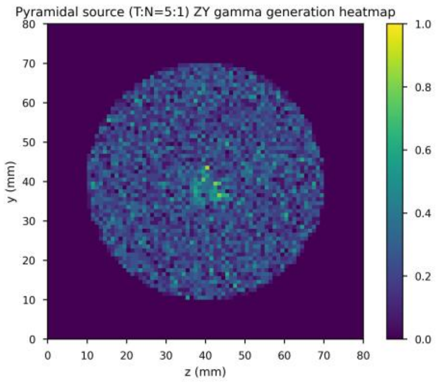


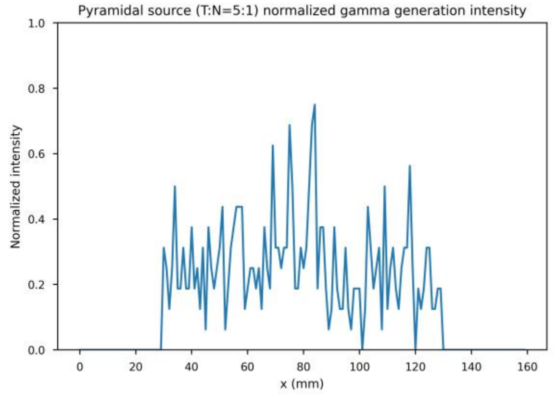




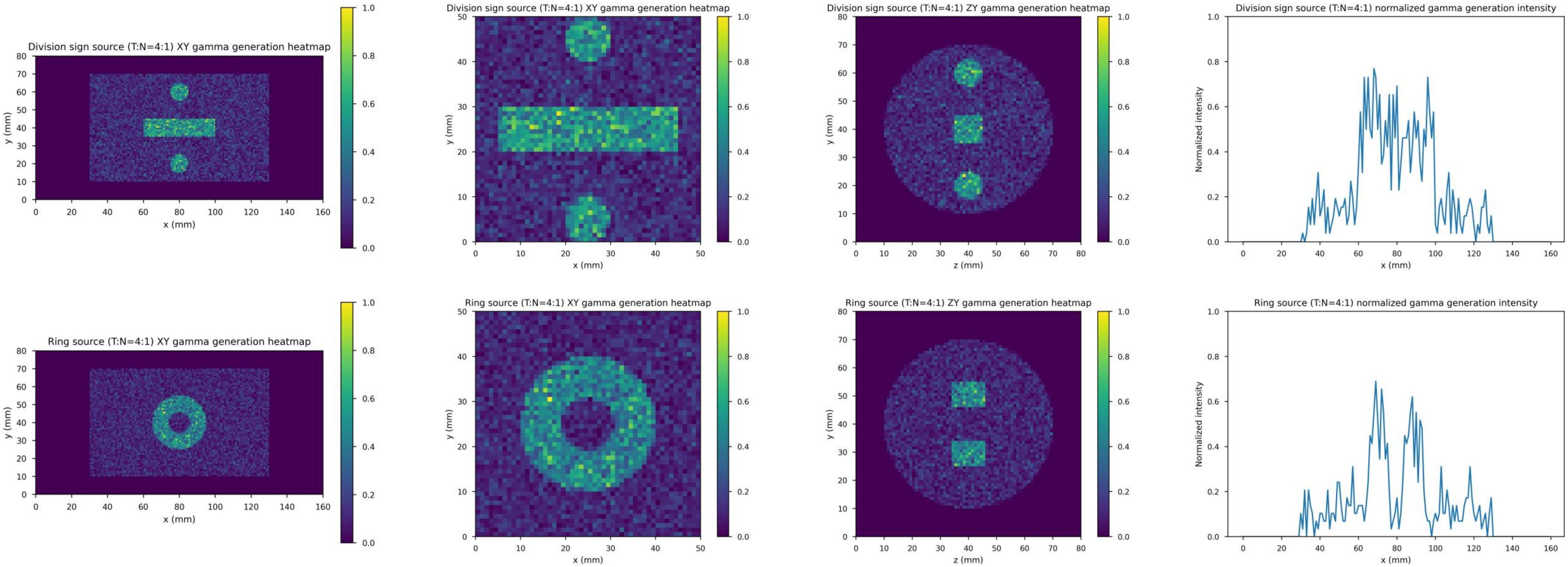








Some source geometries



New detector geometries

New geometries to reduce z-stretching and improve 3D reconstruction:

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

- 6 four-layers detectors geometry (4 frontal, 2 at ±60°); best reconstruction but currently more expensive

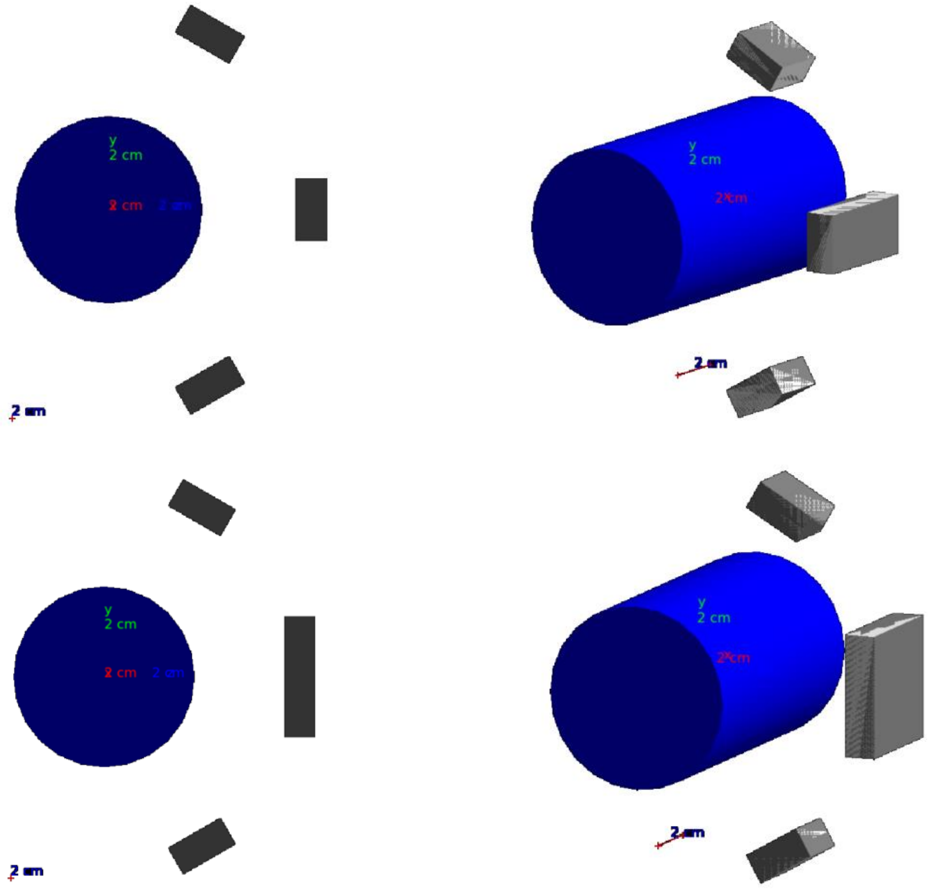
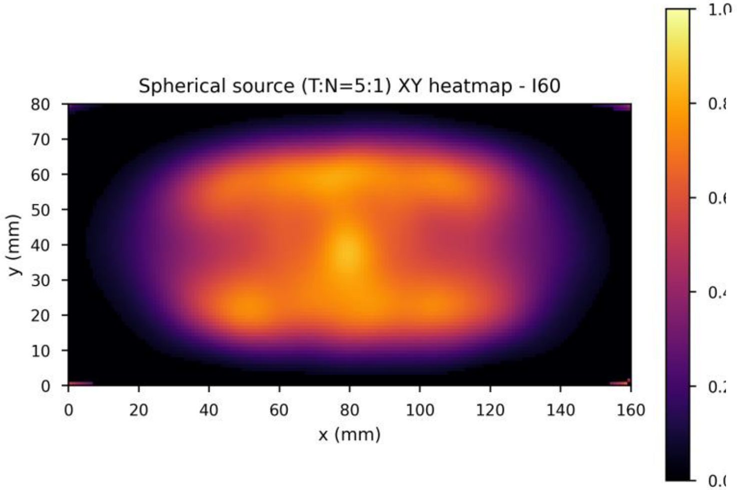
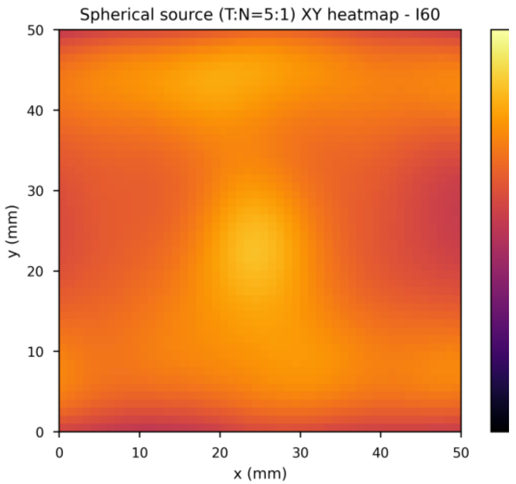
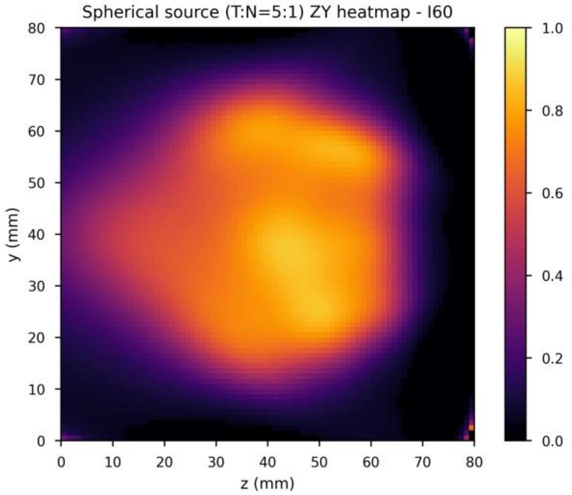


Image reconstruction with MLEM algorithm: spherical distribution with T:N=5:1

160x80x80 voxels images. Each voxel has a 1 mm side.







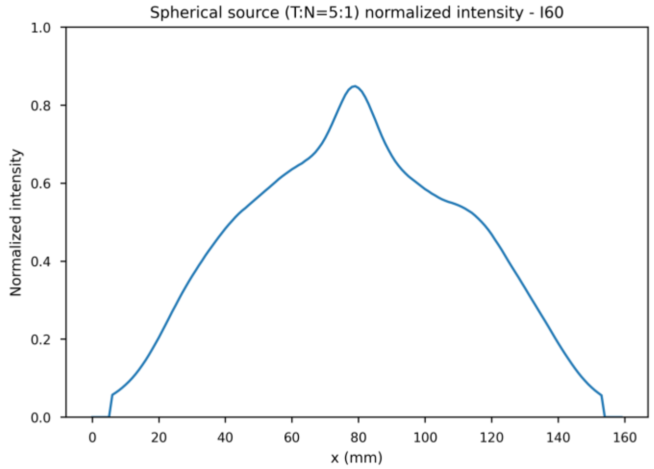
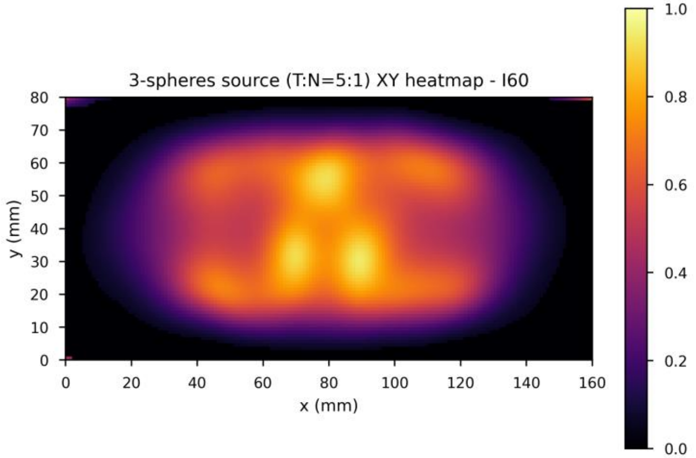
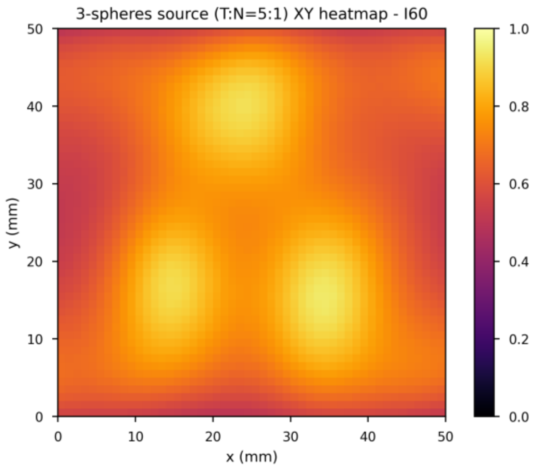
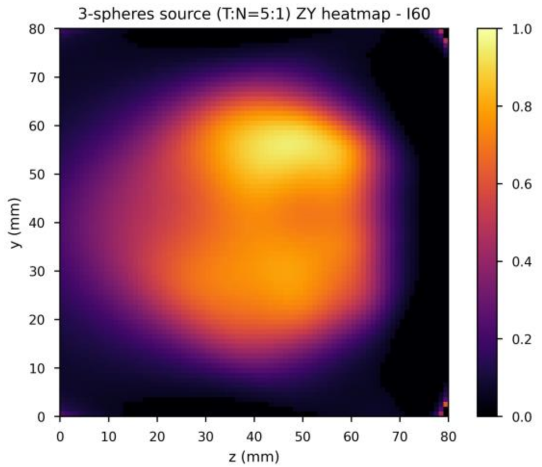


Image reconstruction with MLEM algorithm: 3-spheres distribution with T:N=5:1







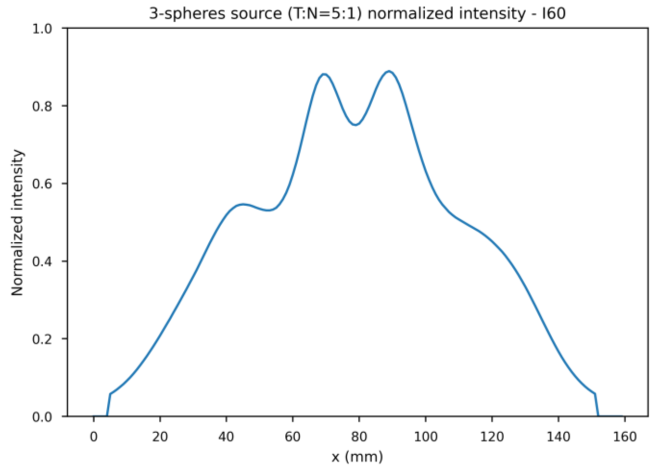
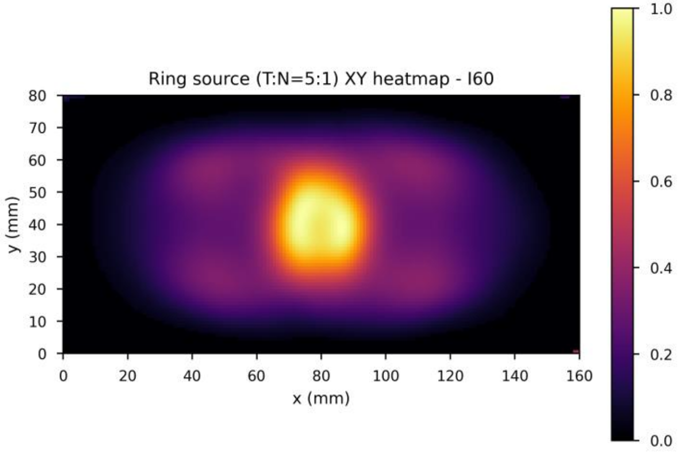
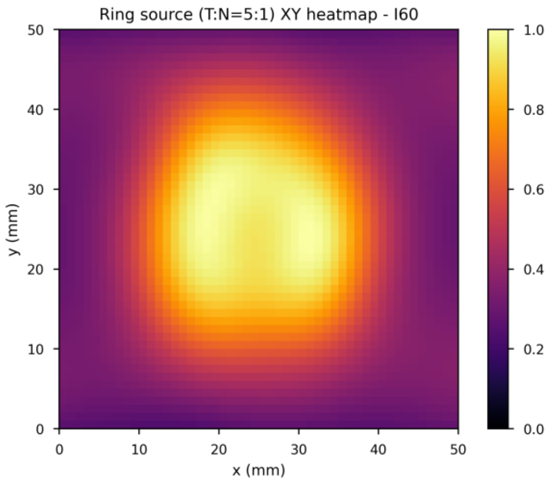
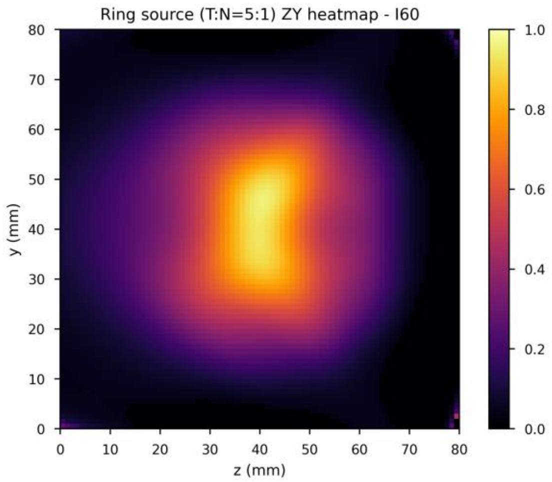
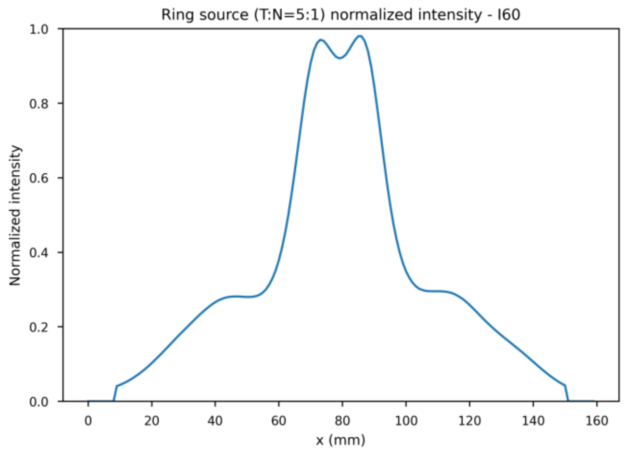


Image reconstruction with MLEM algorithm: ring distribution with T:N=5:1







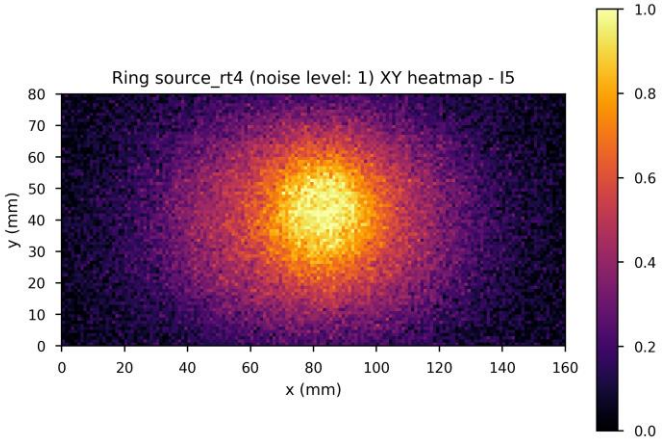


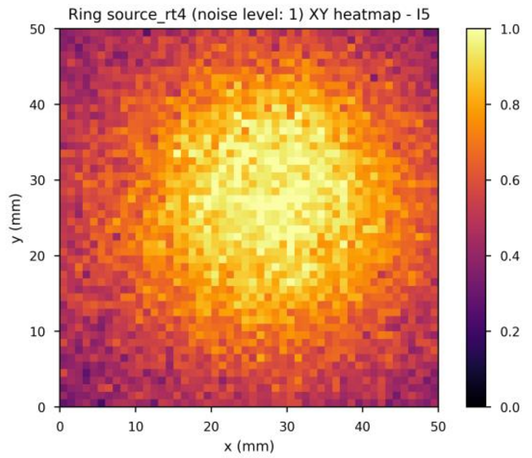
Data augmentation: roto-translations and white Gaussian noise addition

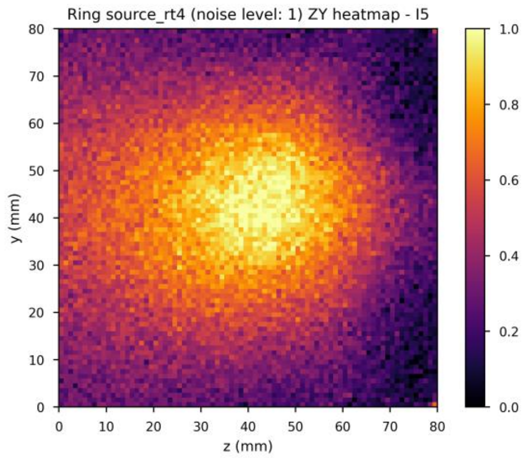
- Starting from 20 different tumor source geometries, 71 original 3D images were obtained considering different T:N ratios (3:1, 4:1, 5:1, ∞:1)

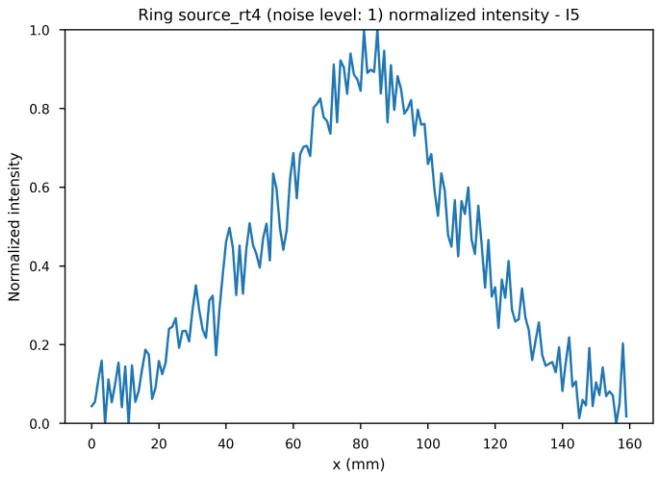
- for each of the 71 original images, 4 roto-translations of the tumor source were considered (71x5 images)

- for each of the images, 100 images were obtained by adding three different levels of white Gaussian noise (71x5x101=35855 images)

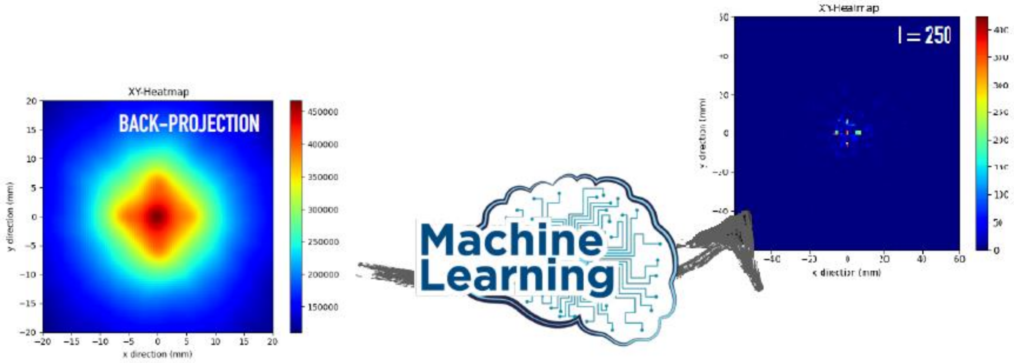


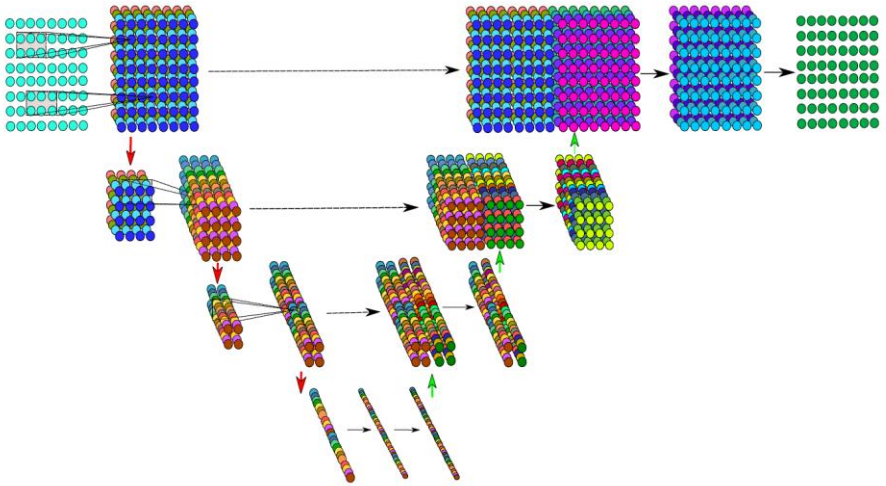






DNN model for image reconstruction





A data set of reconstructed images will be obtained from the data generated with the GEANT4 simulation toolkit.

This data set will be used to train models like U-Net and EM-Net with the aim of reconstructing the accurate source distribution.

Finally, the models' performance and the reconstructed source distribution will be estimated.

3D U-Net variants for image denoising

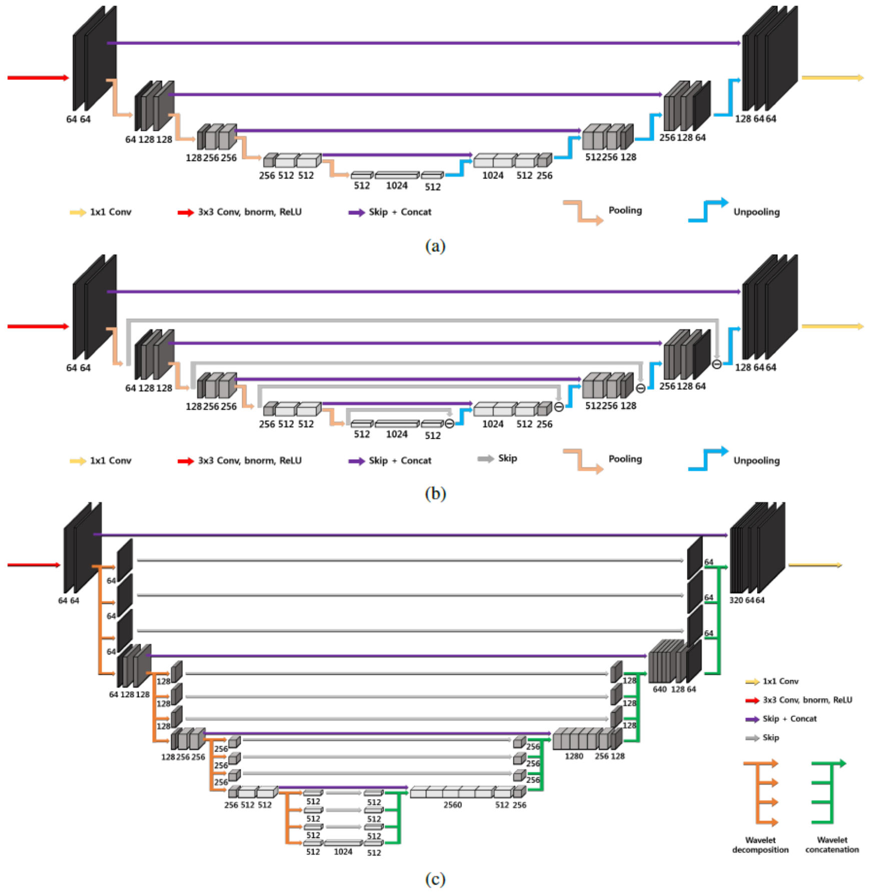
U-Net and improved versions will be used for image denoising:

(a) 3D classic U-Net

(b) 3D dual frame U-Net

(c) 3D tight frame U-Net with Haar filter bank

The input images will be the results of one of the first iterations (ideally the backprojection images) or the images produced by the 3D Compton EM-Net in the next slide.



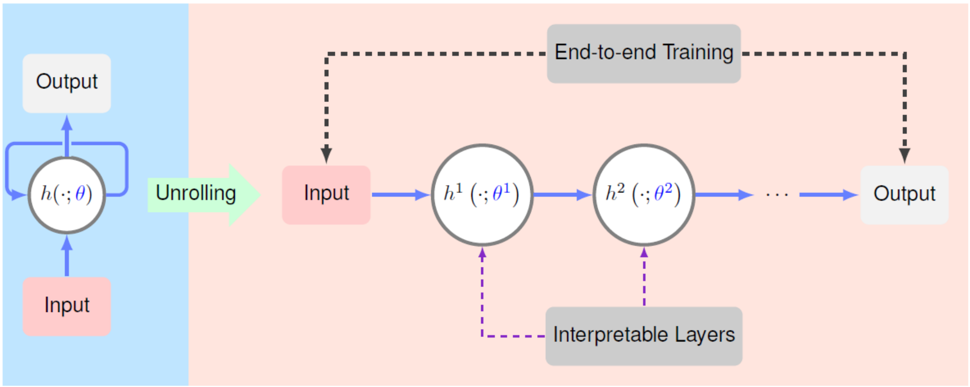
3D Compton EM-Net for image reconstruction (under development)

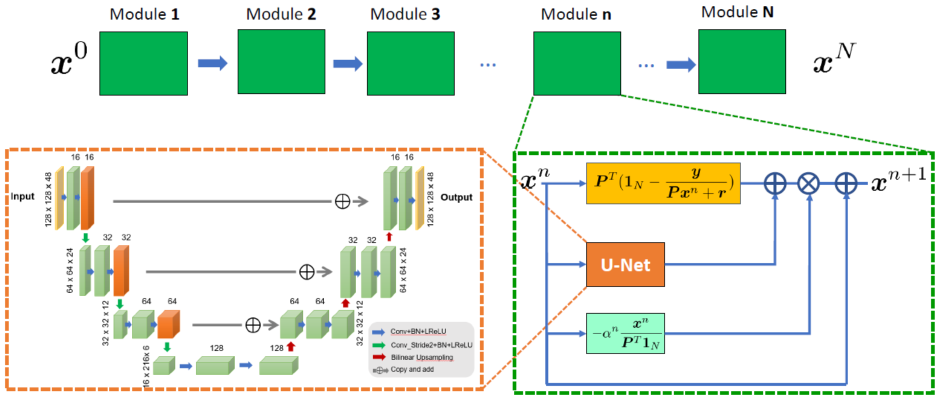
3D Compton MLEM unrolling with C++/CUDA PyTorch Extensions.

10X expected improvement of the reconstruction at a certain iteration.

4-5 modules of the algorithm should provide an image comparable to the one obtained with 40-50 iterations of the MLEM algorithm.

Reconstruction time reduction: from ~ 25-30 min to ~ 2 min. The resulting reconstruction can be further improved by applying the U-Net variants in the previous slide to the output image.

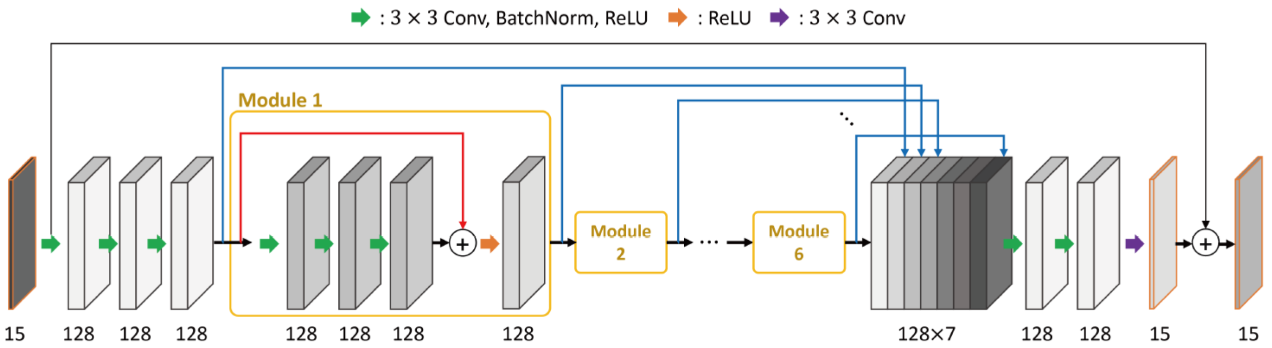




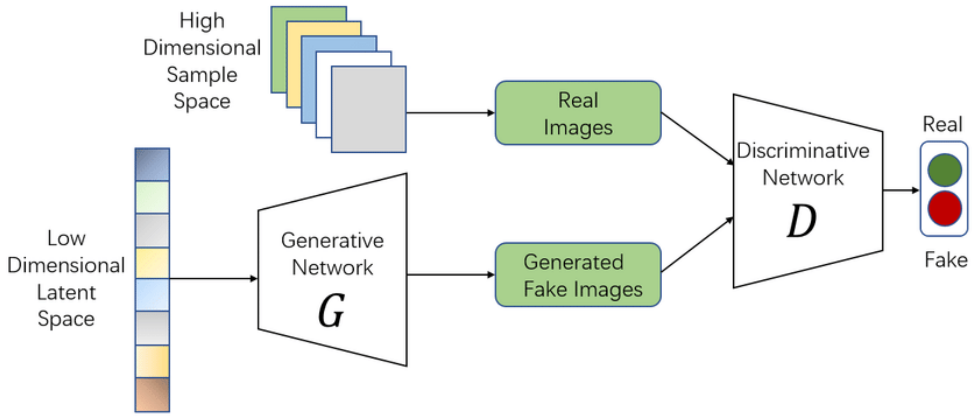
Other architectures (time permitting)

Other possible architectures that could be employed:

- 3D ResNet and 3D WavResNet



- Generative models (GANs, …)



Thanks for the attention