Toward a generic approach for dose distribution recovery by using Deep Learning and GPU-based Geant4 simulations

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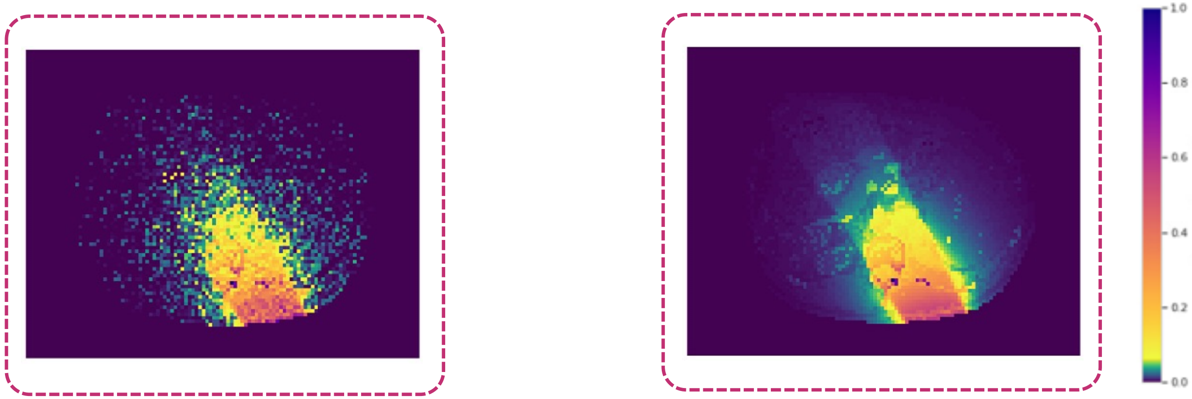
Motivations

MC simulations & Temporal complexity

Low sampling (LS) Vs **High sampling (HS)**



Features	Values	
Number of particules	5.10^5	5.10^8
Uncertainty average	60±30%	2±0.7%
Simulation time (Gate) – CPU*	40s	~10h

***CPU**: CPU core Intel Xeon W-2223 3,6GHz

MC Denoising

Previous studies (1)

❖ **Standard approaches: Filtering based**

[1]

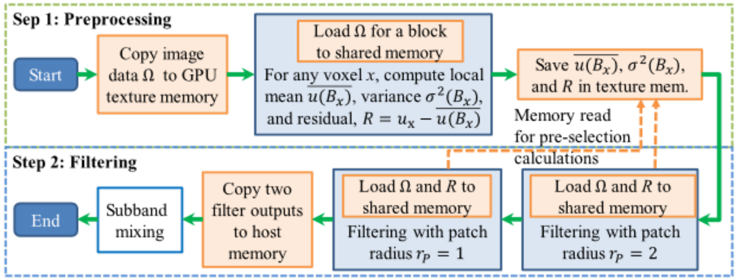


Fig. 1 GPU ANLM filter algorithm workflow diagram. All memory operations are shaded in orange; the steps executed in the GPU are shaded in light-blue.

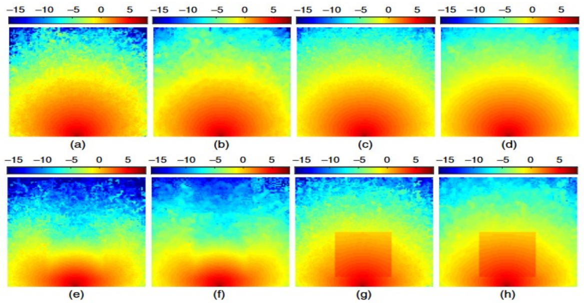


Fig. 3 Comparisons between fluence cross-sectional plots before and after denoising in three benchmarks: (c and d) a homogeneous domain (B1), (e and f) a cubic domain with an absorbing inclusion (B2) or (g and h) a reflective inclusion (B3). In each pair, we show the fluence maps before (c, e, and g) and after (d, f, and h) the denoising filter. For visual comparison, we also show the plots for running 10^6 photons for the homogeneous case in (a) and its denoised version in (b). All fluence plots are shown in $\log_{10}$ scale.

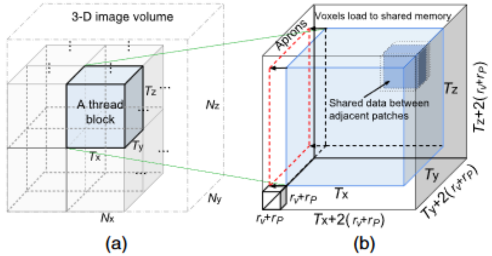


Fig. 2 GPU thread and memory mapping: (a) image-to-thread space mapping and (b) image subvolumes loaded to the shared memory. In (a), an $N_x \times N_y \times N_z$ image volume is partitioned into blocks of size $T_x \times T_y \times T_z$, with each block filtered by a thread block[43] of the same size and each voxel in the block updated by a single thread. In (b), filtering a single block requires to load not only the block-mapped voxels (light-blue) but also the voxels within a margin, referred to as the "aprons," determined by the radii of the patch (r_P) and search area (r_V).

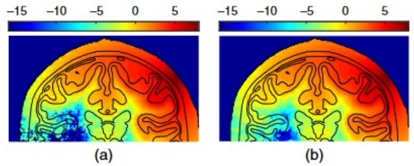


Fig. 5 Comparisons between the simulated fluence images with 10^8 photons, in coronal views, in a 19.5-year-old brain atlas (a) before and (b) after denoising. The fluence is shown in $\log_{10}$ scale.

[1] Y. Yuan, L. Yu, and Q. Fang, "Denoising in Monte Carlo Photon Transport Simulations Using GPU-accelerated Adaptive Non-Local Mean Filter," in Biophotonics Congress: Biomedical Optics Congress 2018 (Microscopy/Translational/Brain/OTS)

MC Denoising

Previous studies (2)

❖ **Recent approaches:** ***Deep Learning based***

[2]

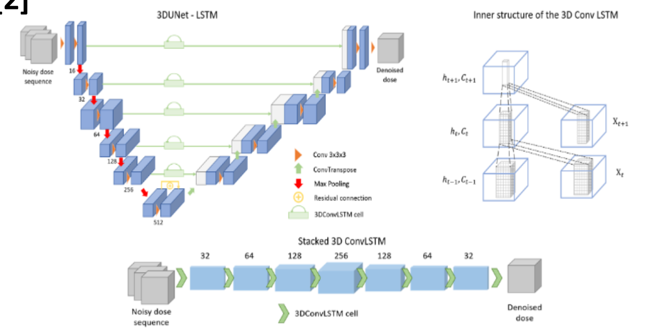
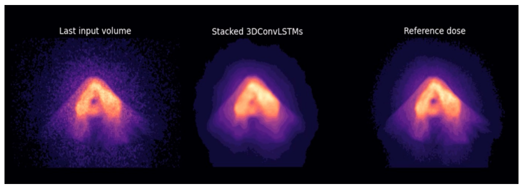


Fig. 1. Proposed architectures and inner structure of the 3D ConvLSTM. The number of output channels after each block appears above or below the layers' output volumes.



[3]

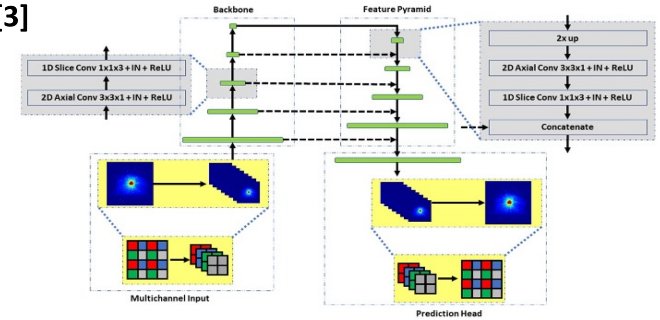
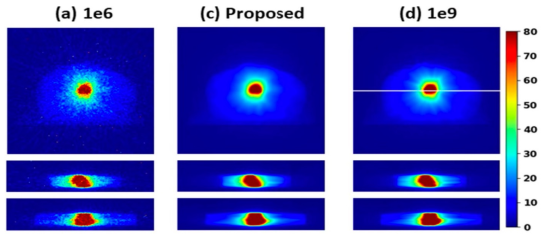


Figure 1. Network architecture illustration. There are four major components: multichannel input, backbone, feature pyramid and prediction head. The multichannel input is consisting of a voxel unshuffle operator that can effectively reduce the feature map size. In the backbone and feature pyramid, all the 3D volumetric convolution operators are decomposed into a 2D axial convolution operator and a 1D slice convolution operator. The prediction head contains another decomposed convolutional layer and a vo



[4]

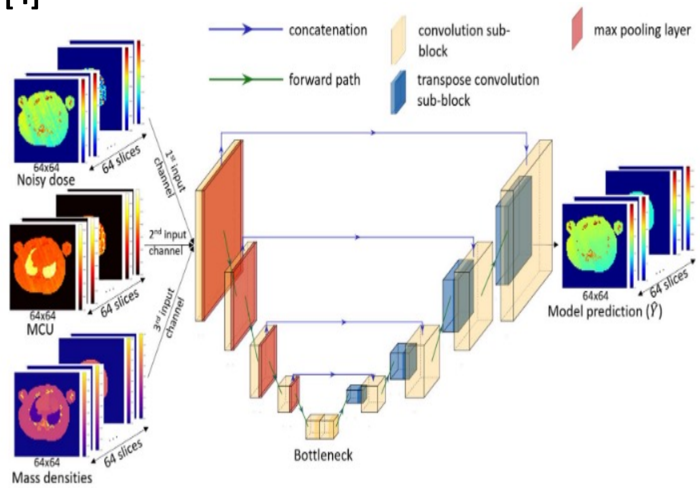


Figure 1. Model architecture overview. The model can take three inputs: the noisy dose distribution, corresponding MCU map and mass density map. Max pooling, convolution and transpose convolution sub-blocks are depicted by dark orange, light yellow and light blue blocks, respectively. The width of the (transpose) convolution blocks provides relative information on the number of filters used.

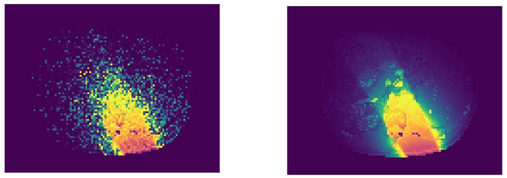
Sensitivity to the MC setup configurations !

[2] S. Martinot *et al.*, "High-Particle Simulation of Monte-Carlo Dose Distribution with 3D ConvLSTMs," in MICCAI 2021.
[3] T. Bai *et al.*, "Deep dose plugin: towards real-time Monte Carlo dose calculation through a deep learning-based denoising algorithm," Mach. Learn. Sci. Technol., vol. 2, no. 2, p. 025033, 2021.
[4] van Dijk, Robert HW, et al. "A novel multichannel deep learning model for fast denoising of Monte Carlo dose calculations: preclinical applications." *Physics in Medicine & Biology* 67.16, 2022.

Our preliminary proposed approach

Aims & Processing

❖ **Aims**



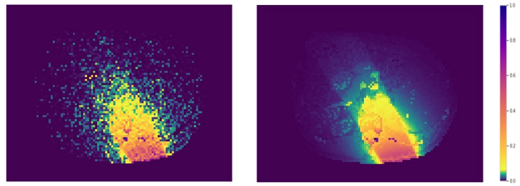
LS **HS**

- ○ **Extreme case (highly undersampled)**
- ○ **Complex distribution (heterogeneity)**
- ○ **Inpainting / denoising**
- ○ **Generic approach (reduce the sensitivity to configuration setups)**

❖ **MC simulations (GGEMS*)**

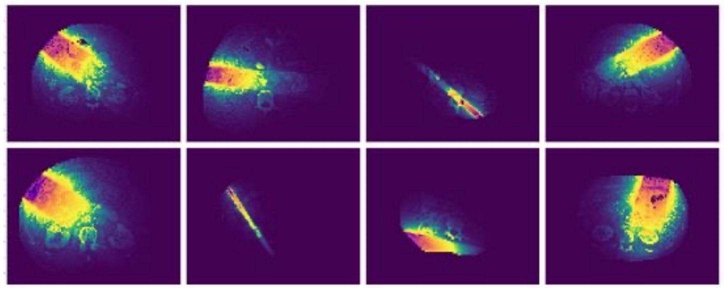
- **Geant4 GPU-based MC simulation**

- NVIDIA GTX3090 card
- 82 CT scans (abdominal)
- Cone-beam photon source
- $5\text{x}10^5$ photons (LS)
- $5\text{x}10^8$ photons (HS)



LS: uncert. 60±30% **HS:** uncert. 2±0,7%

- Different simulation setups :
  - Beam aperture (°) in [0,5, 4,99]
  - Angulation view (°) in [-180, +180]
  - Energy values (keV) in [50, 999]

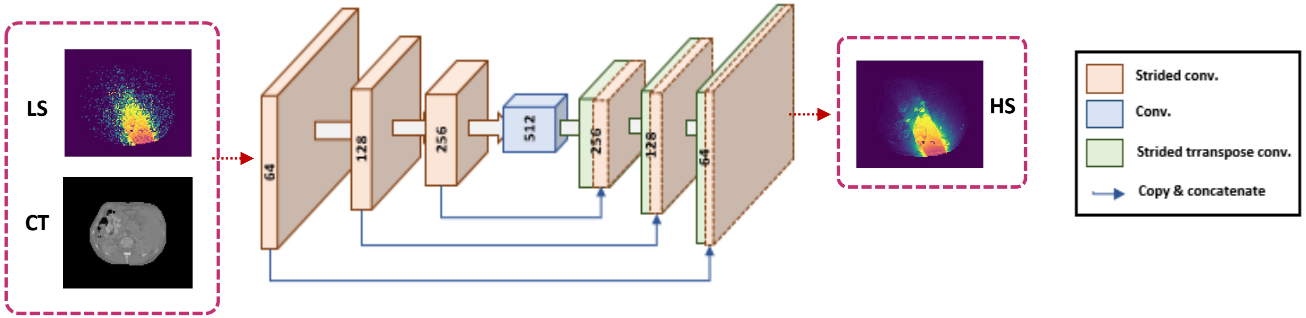


* https://ggems.fr, Bert et al. Geant4-based Monte Carlo simulations on GPU for medical applications *Phys Med Biol* **58** 5593–611, 2013

Our preliminary proposed approach

Classical deep-based approach

❖ ***MC-UNet: Multi-channel & Unet based architecture***



❖ **Training dataset**

- Arbitrary number of 2D slices for each patient (CT & Dose maps)
- Normalized intensity ([0,1])
- Dataset (**DS**) :
  - 10000 samples with energy values in **[50, 999]** (keV)
  - shuffled samples (2D LS, 2D HS, 2D CT)
  - 80% training, 20% validation

❖ **Training**

- Adam optimizer, 10-4 learning rate,
- Training:
  - NVIDIA GPU GeForce GTX 1080
  - 200 epochs, 10 batches (6hours)

❖ **Evaluation**

- Using the 20% validation samples
- MSE and absolute error

Our preliminary proposed approach

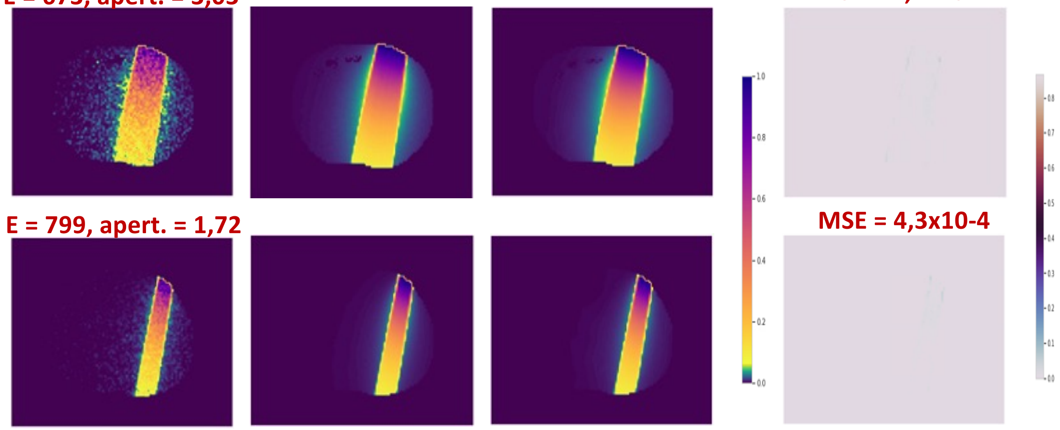
MC-Unet performances (1)

No sensitivity to apertures, beam angles, …

- ***Same angle***

E = 673, apert. = 3,03 — MSE = 7,7x10-4

E = 799, apert. = 1,72 — MSE = 4,3x10-4

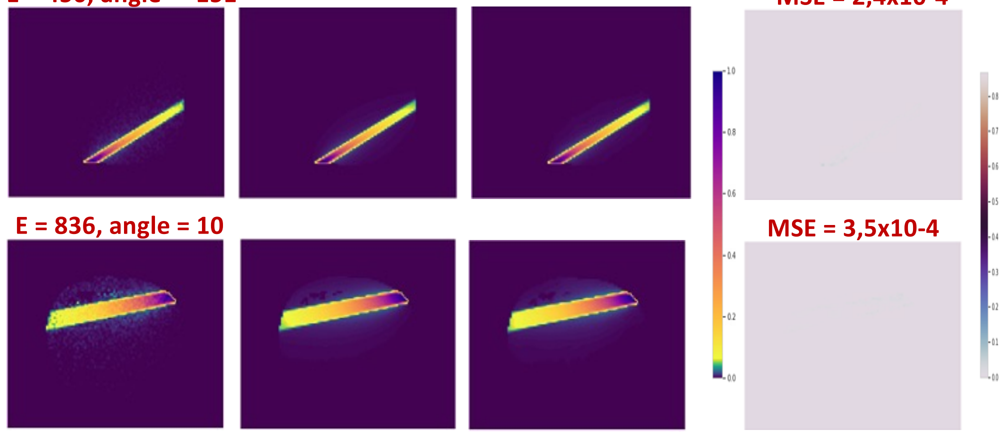


Input (LS) | Ground Truth (HS) | MC-UNet prediction | MC-UNet error map

- ***Same aperture***

E = 450, angle = -151 — MSE = 2,4x10-4

E = 836, angle = 10 — MSE = 3,5x10-4

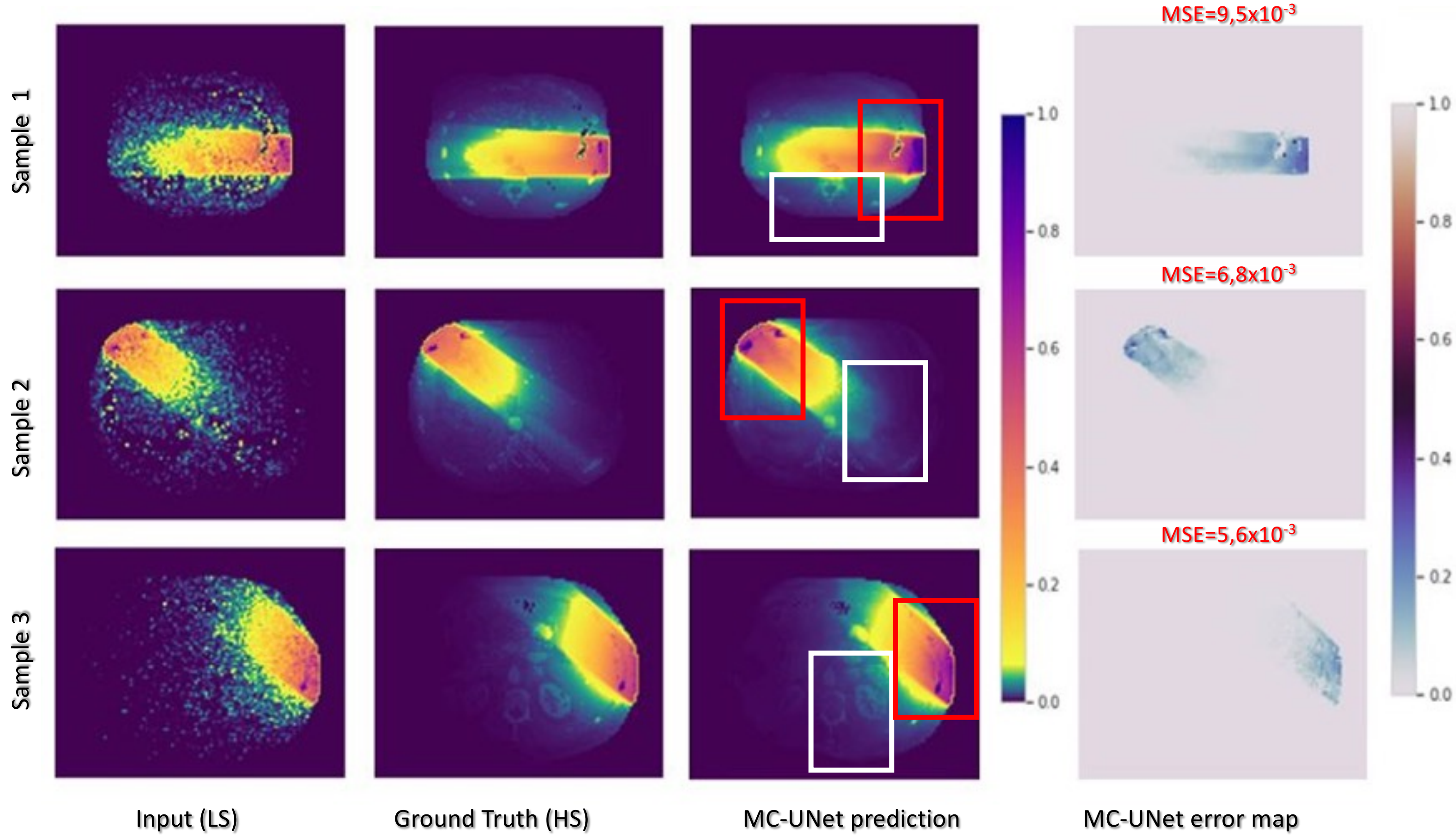


Input (LS) | Ground Truth (HS) | MC-UNet prediction | MC-UNet error map

Our preliminary proposed approach

MC-Unet performances (2)

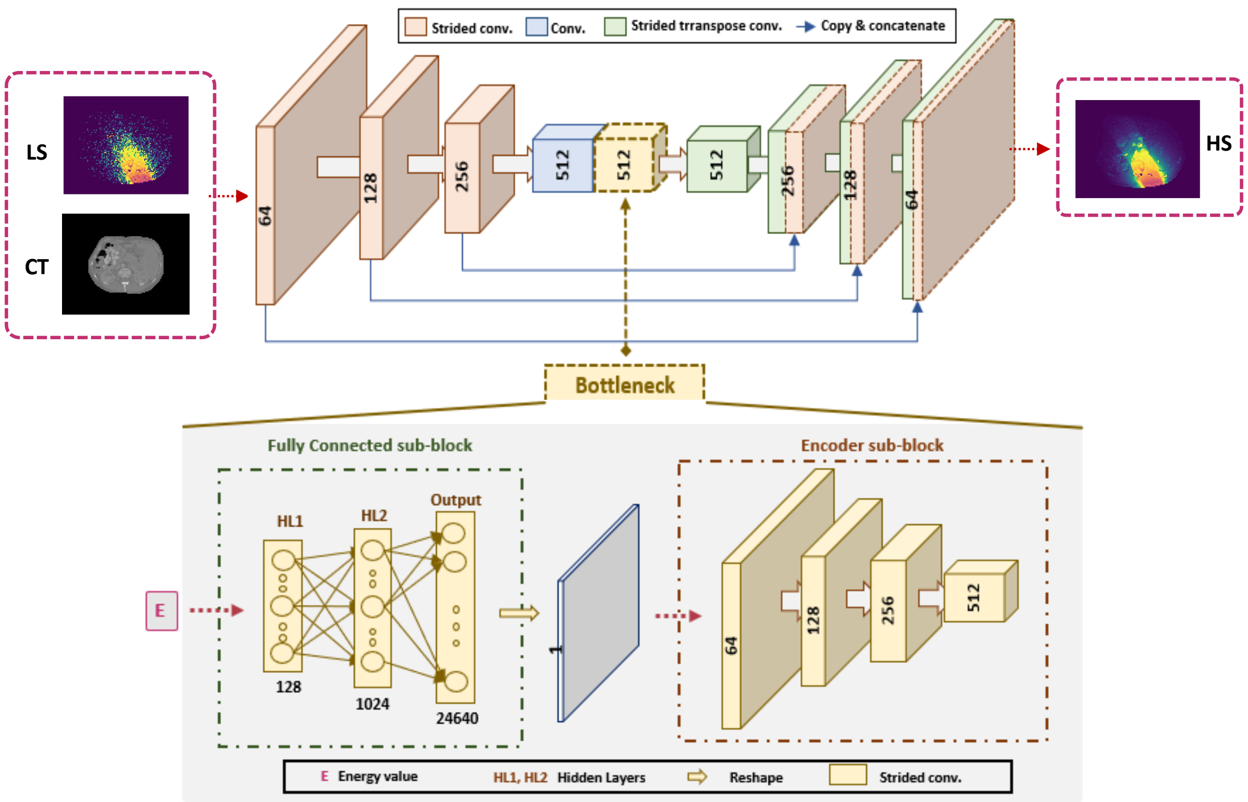
Issue due to the diverse energy values : Depth dose curve !



Our preliminary proposed approach

Proposed architecture

❖ ***CMC-UNet: Multi-channel & Energy conditioned & Unet based architecture***



❖ **Training dataset**

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  - 10000 samples with energy values in **[50, 999]** (keV)
  - shuffled samples (2D LS, 2D HS, 2D CT)
  - 80% training, 20% validation

❖ **Training**

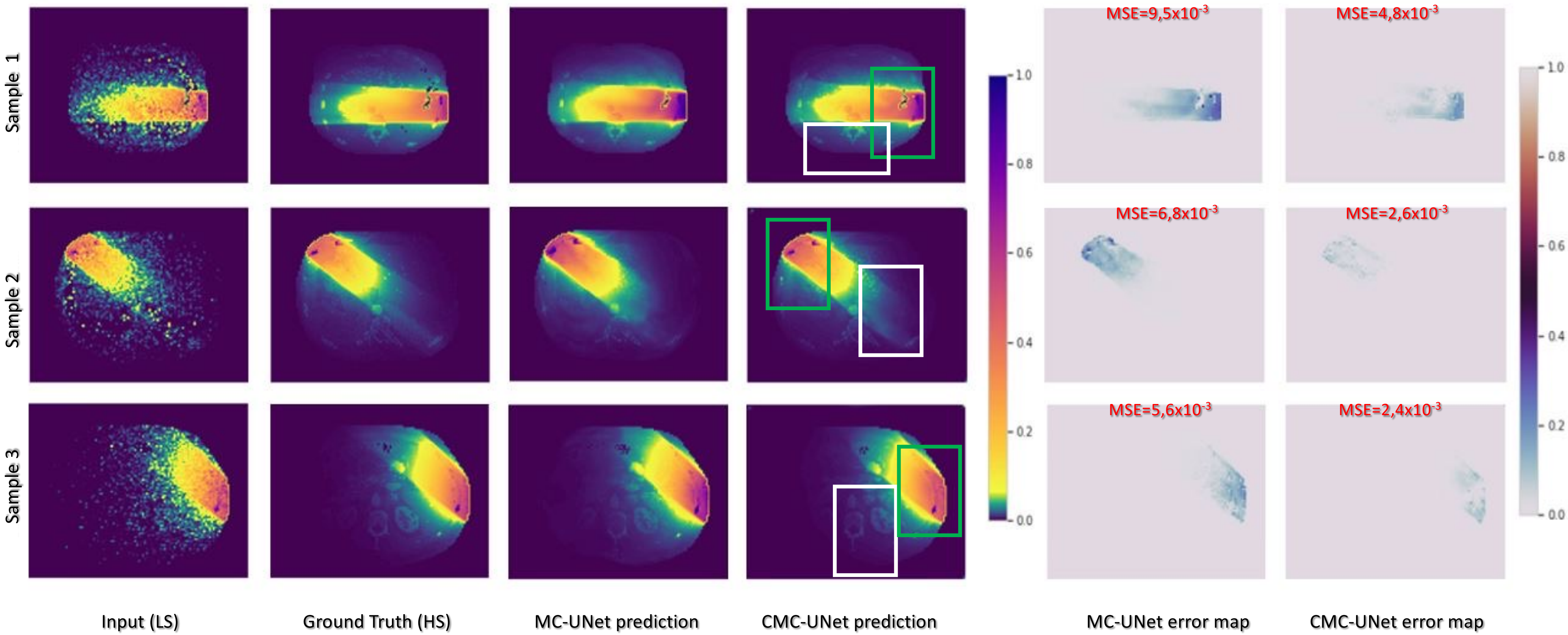
- Adam optimizer, 10-4 learning rate,
- Training:
  - NVIDIA GPU GeForce GTX 1080
  - 200 epochs, 10 batches (15hours)

❖ **Evaluation**

- Using the 20% validation samples
- SSIM and absolute error

Preliminary results

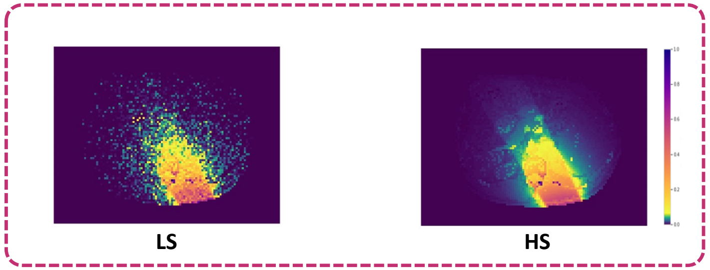
CMC-UNet *vs* MC-UNet



Conclusions

❖ **Aims**

- **Extreme case (highly undersampled)**
- **Complex distribution (heterogeneity)**
- **Inpainting / denoising**
- **Generic approach – Improve abs. err. values**



❖ **Improve model's genericity**

- Encode other information to the model (improve the absolute error values)
- Train for different CT volumes (head, neck, …)

❖ **Future work**

- Compare with other works (ex. [4] Van Dijk et al.) and standard filtering methods
- Test for different medical applications

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