A Fast and Generic Energy-Shifting Transformer for Hybrid Monte Carlo Radiotherapy Dose Calculation

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ACTION Team : *Multimodal Imaging Guided Therapeutic Action in Oncology*



Medical physics

Radiation therapy



External beam radiotherapy

Medical imaging





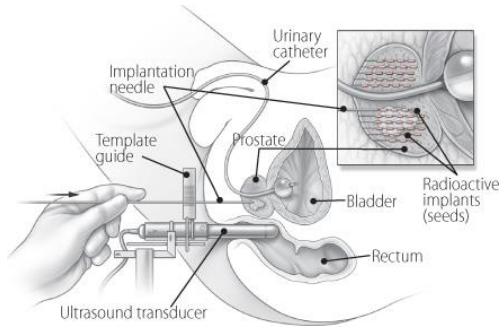
Nuclear medical imaging



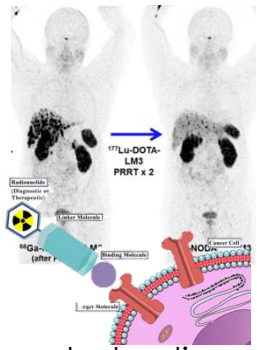


X-ray interventional radiology





Intraoperative radiotherapy

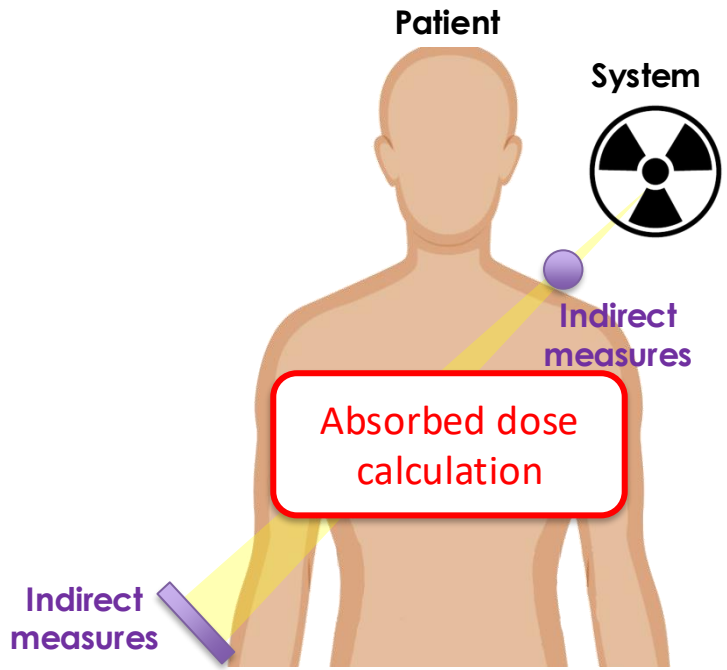


Targeted radionuclide therapy

Clinical issue

Optimize radiation exposure (dose):

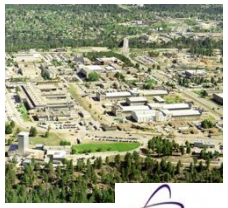
- ❑ **Maximize** efficiency (processing, image)
- ❑ **Minimizing** toxicity (patient and staff)

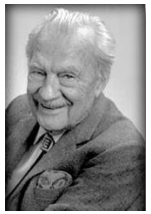


Limits

- **Not optimized treatment** (toxicity)
- **Explore** new innovative treatment

Monte Carlo simulation





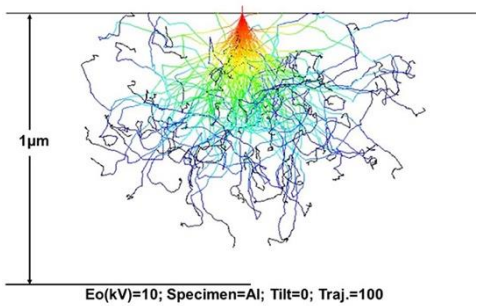
Nicholas Metropolis
(1915-1999)



Stanislaw Ulam
(1909-1984)



Joseph von Neumann
(1903-1957)



Particle **physics** transport in matter



Random **sampling**

$$\epsilon = f(\frac{1}{\sqrt{N}})$$

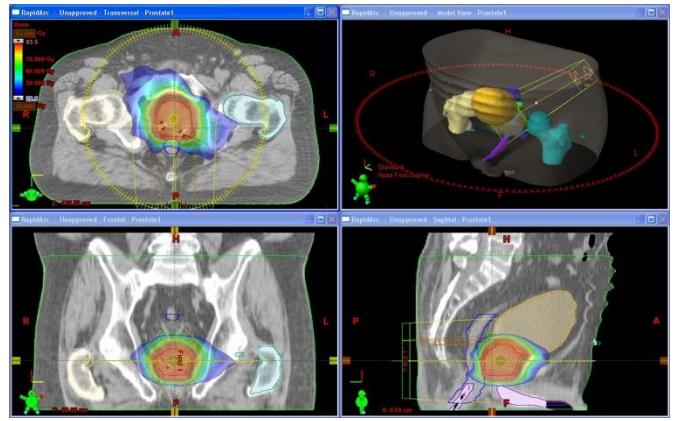
Law of large numbers

Medical physics
The early 70's marked the rise of Monte Carlo simulations for medical physics applications.

Computation time

Clinical use

Dose models



Eclipse™ | Varian Medical Systems

Deterministic model

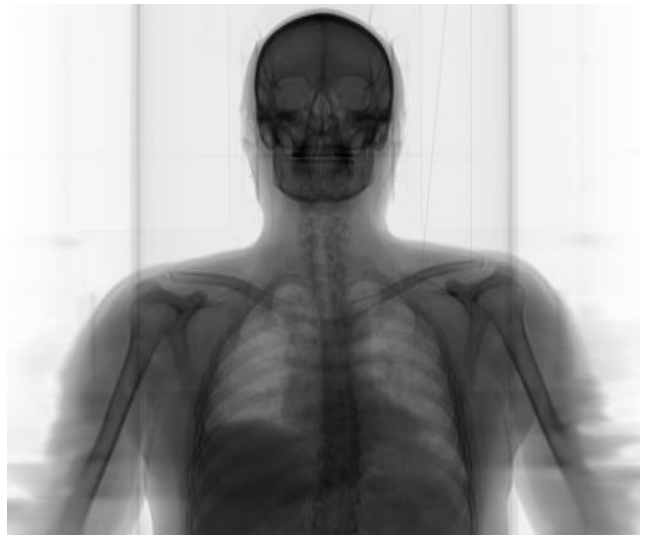
- Acuros® XB [1]
- Anisotropic Analytical Algorithm [Eclipse]
- Collapsed Cone Convolution [2]

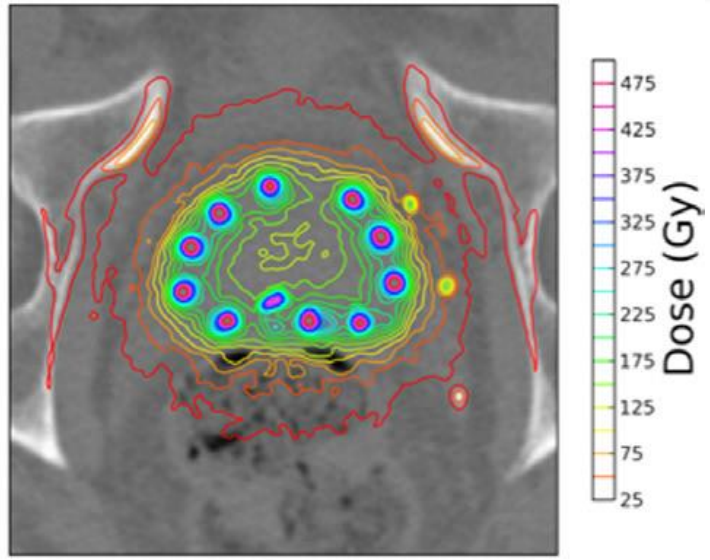
- Accurate
- Fast
- Limited domain (not robust)
- Tissue/air, tissue/bone, tissue/metal implant
- 6% bone, 10% lung [1][2]

*[1] **Han**, T., Mikell, J.K., Salehpour, M., Mourtada, F., 2011. **Med Phys** 38, 2651–2664.*
*[2] **Calvo**, O.I., Gutiérrez, A.N., Stathakis, S., Esquivel, C., Papanikolaou, N., 2012. **J Appl Clin Med Phys** 13, 3751.*

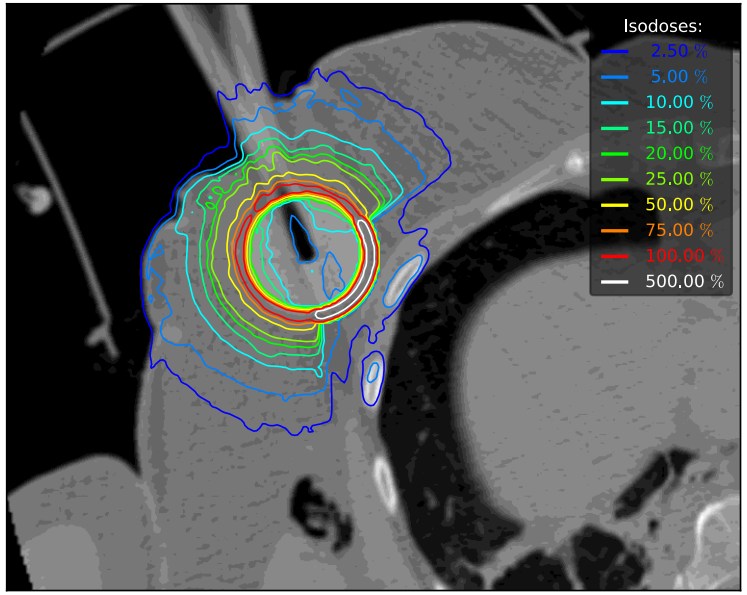
Examples: Monte Carlo in Medical physics

DDR
12x10^9 photons
24 days
One CPU core



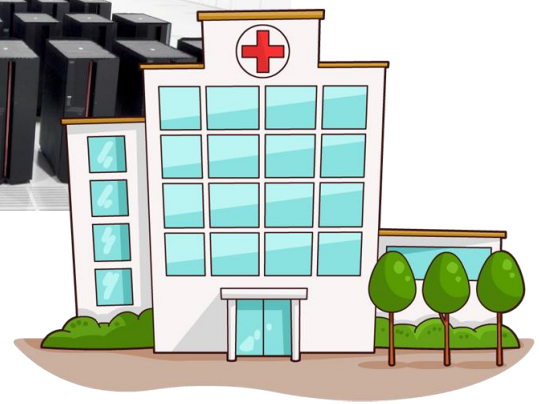


Brachytherapy
15 hours
One CPU core



IORT
20 hours
One CPU core





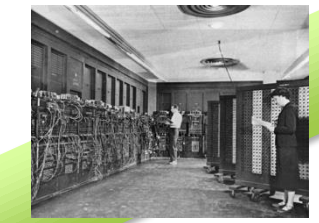
- Patient workflow
- Workspace
- Financial burden
- Availability issue

Improving Monte Carlo efficiency

Monte Carlo efficiency

- For about 50 years
- Working on MC efficiency
- Variance Reduction Technique
- Parallel computing

Computing era (origin)



1946 ENIAC

Cluster computing era



1977

GPU computing era



2008, CUDA, NVIDIA
GPGPU: General-Purpose computing on GPU

A new era: Artificial Intelligence



Deep Learning

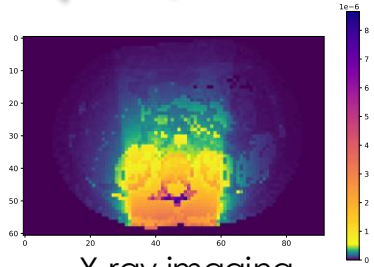
GPU-based Monte Carlo

- GPUMCD [1]
- gDPM [2]
- GMC [3]
- **GGEMS [4]**

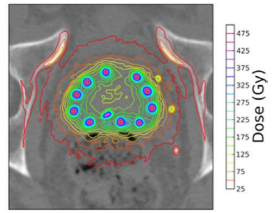
Bert et al. 2013, PMB

- Accurate
- Fast

- Only specific applications
- Not enough fast for adaptative/live inverse planning, monitoring, etc.



X-ray imaging
10 hours (CPU)
10 seconds (GPU)

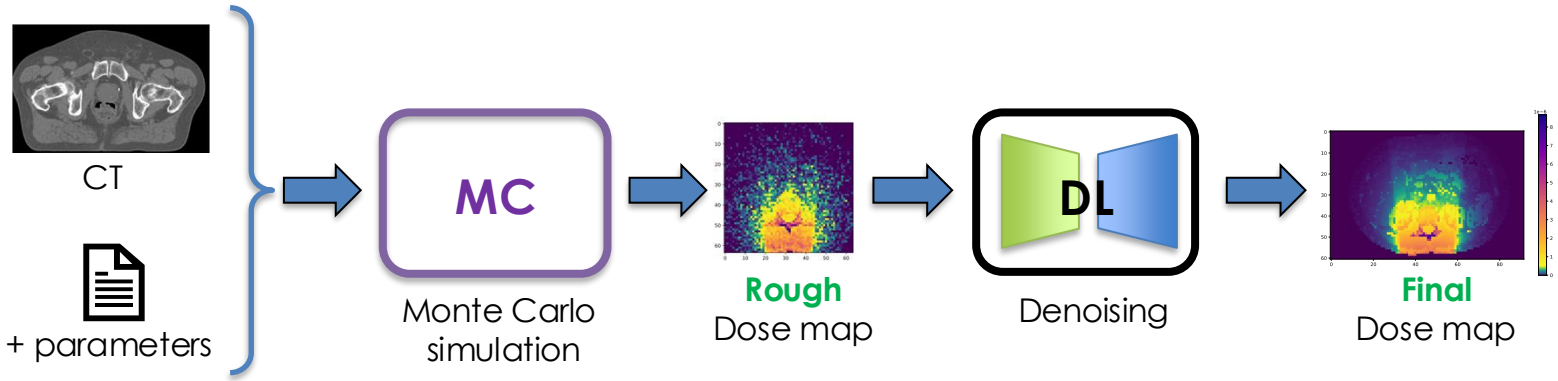


Brachytherapy
15 hours (CPU)
10 seconds (GPU)

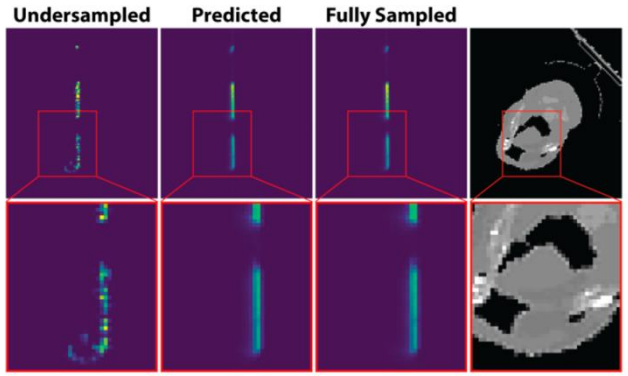
[1] Hissoiny et al., 2011. Med Phys 38, 754–764.
[2] Jia et al. 2011. Phys Med Biol 56(22), 7017-7031.
[3] Jahnke et al. 2012. Phys Med Biol 57, 1217–1229.
[4] Bert et al. 2013. Phys Med Biol 58, 5593–5611.

Low statistics Monte Carlo and deep learning

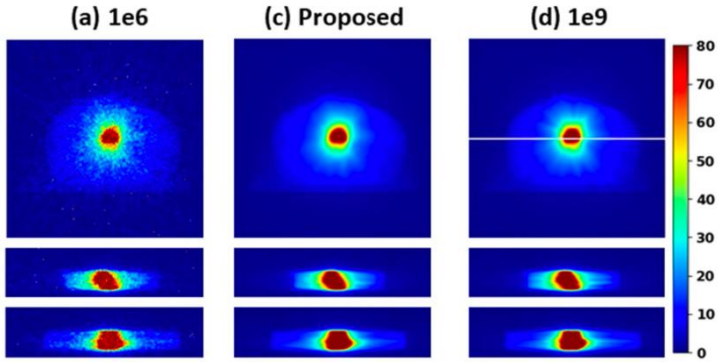
Denoising approach



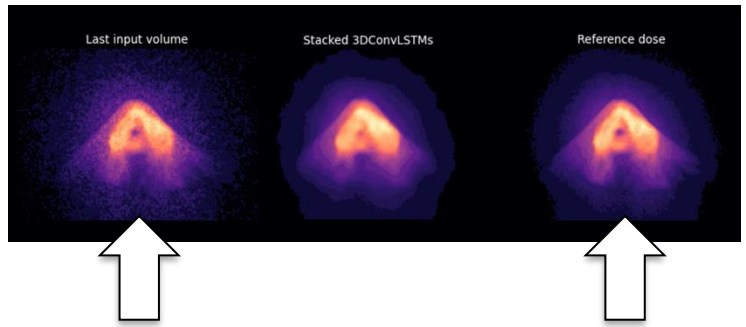
R. Neph, Y. Huang, Y. Yang, and K. Sheng, *Artificial Intelligence in Radiation Therapy*, vol. 11850, pp. 137–145, 2019



T. Bai, B. Wang, D. Nguyen, and S. Jiang, *Mach. Learn.: Sci. Technol.*, vol. 2, no. 2, p. 025033, 2021

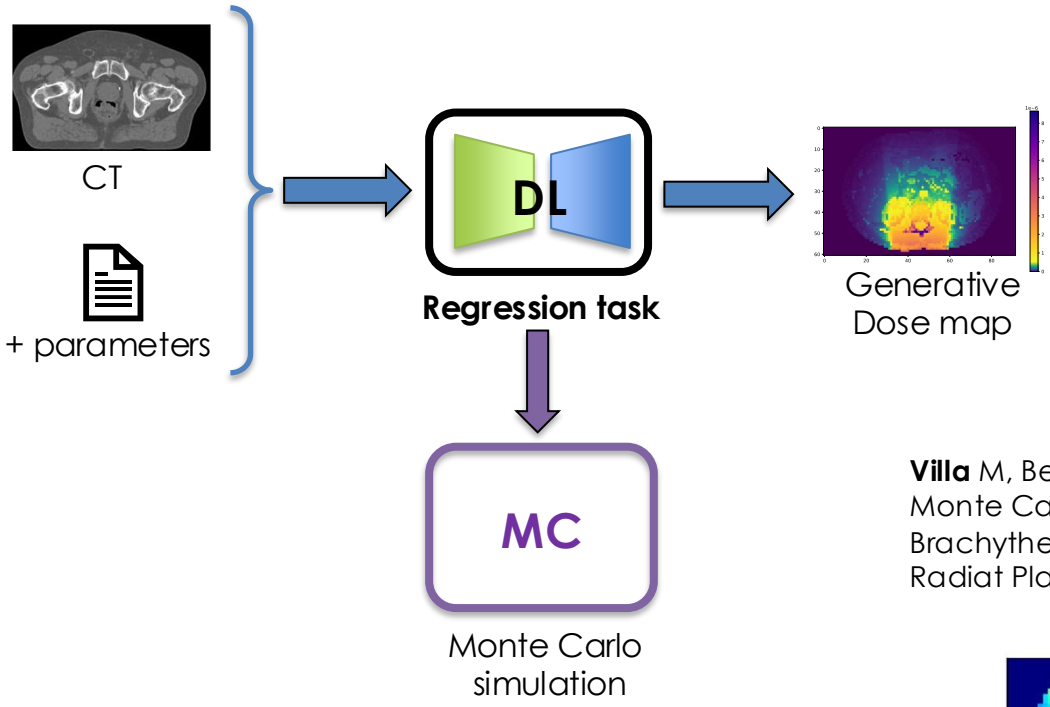


S. Martinot, N. Bus, M. Vakalopoulou, C. Robert, E. Deutsch, and N. Paragios, *Medical Image Computing and Computer Assisted Intervention*, vol. 12904, pp. 499–508, 2021.

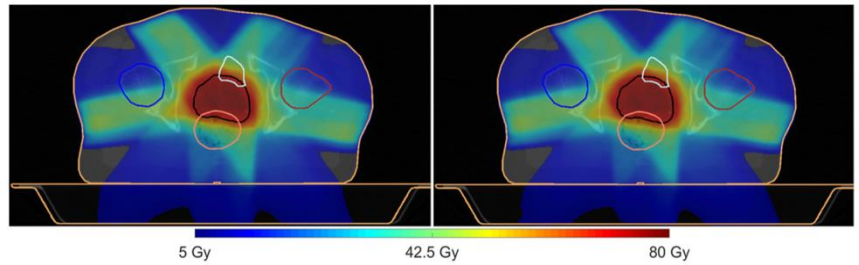


Results depend on the input statistics.

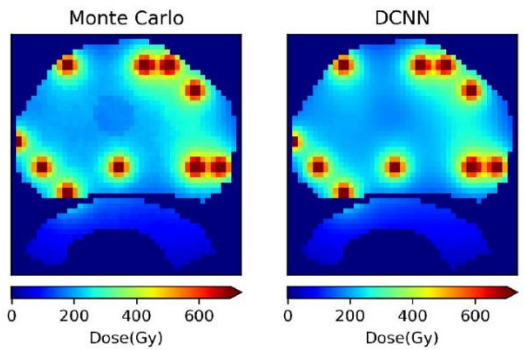
Deep Learning based on MC data



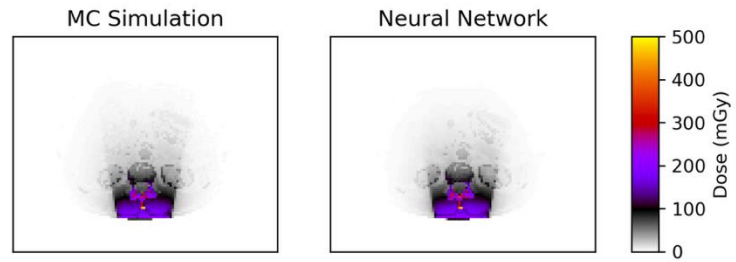
Kontaxis C, et al.. DeepDose: Towards a fast dose calculation engine for radiation therapy using deep learning. Physics in Medicine & Biology. 2020



Villa M, Bert J, Valeri A, Schick U, Visvikis D. Fast Monte Carlo-Based Inverse Planning for Prostate Brachytherapy by Using Deep Learning. IEEE Trans Radiat Plasma Med Sci. 2022.



Villa M, Nasr B, Benoit D, Padoy N, Visvikis D, Bert J. Fast dose calculation in x-ray guided interventions by using deep learning. Phys Med Biol. 2023



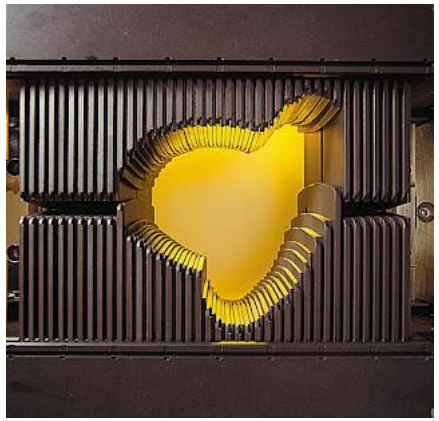
Issues:

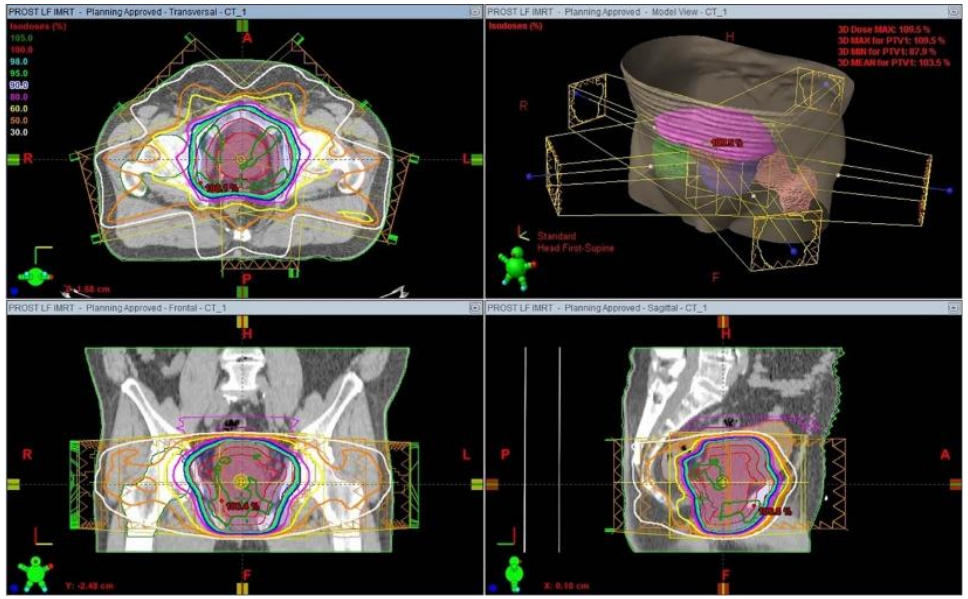
- Get **MC training data**
- **High dependency** on training data set
- **Limited** when too many parameters
- Not **generalizable** (prone to hallucination)

- **Ex. External Beam Radiotherapy!**

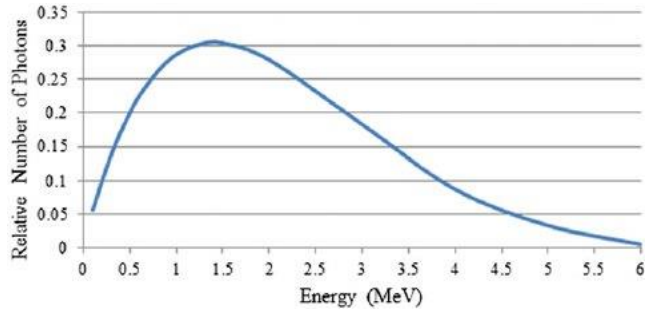
External Beam Radiotherapy







- Multi leaf collimator
- Higher energy (> 1 MeV)
- Electrons
- Less VRT
- Less eff. GPU
- Accuracy

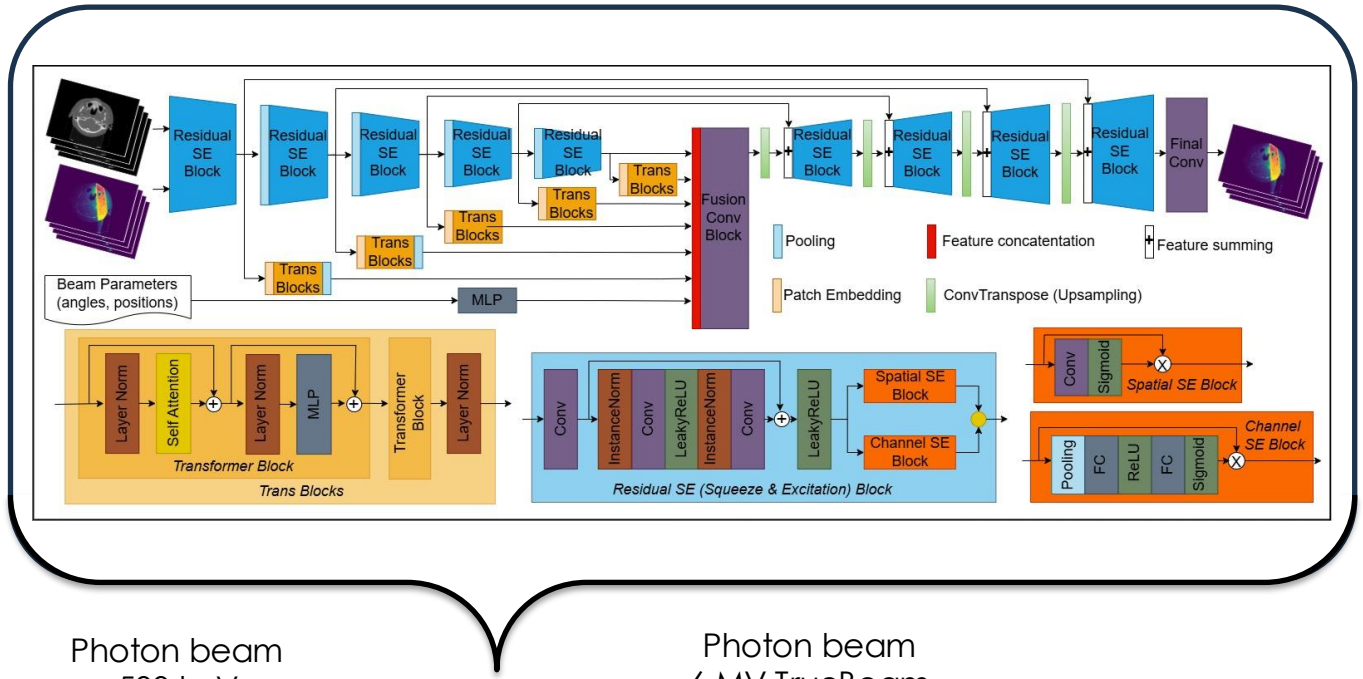


Energy spectrum for a 6 MV beam

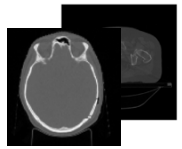
Energy shifting approach

New TransUNetSE3D

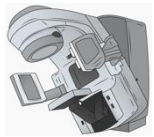
- Baseline: Unet 3D
- Residual block (gradient flow, feature propagation)
- Squeeze-and-Excitation (important features)
- Transformer Blocks (self-attention: global context)



H&N, Pelvis, …



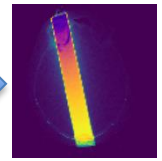
TrueBeam Novalis STX (VARIAN – SIEMENS)



GPU-based MC

GGEMS **[6]**
http://www.ggems.fr

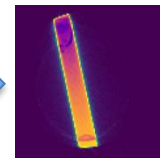
Photon beam 500 keV



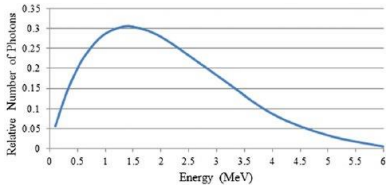
3D dose

Trans.

Photon beam 6 MV TrueBeam



3D dose



MC

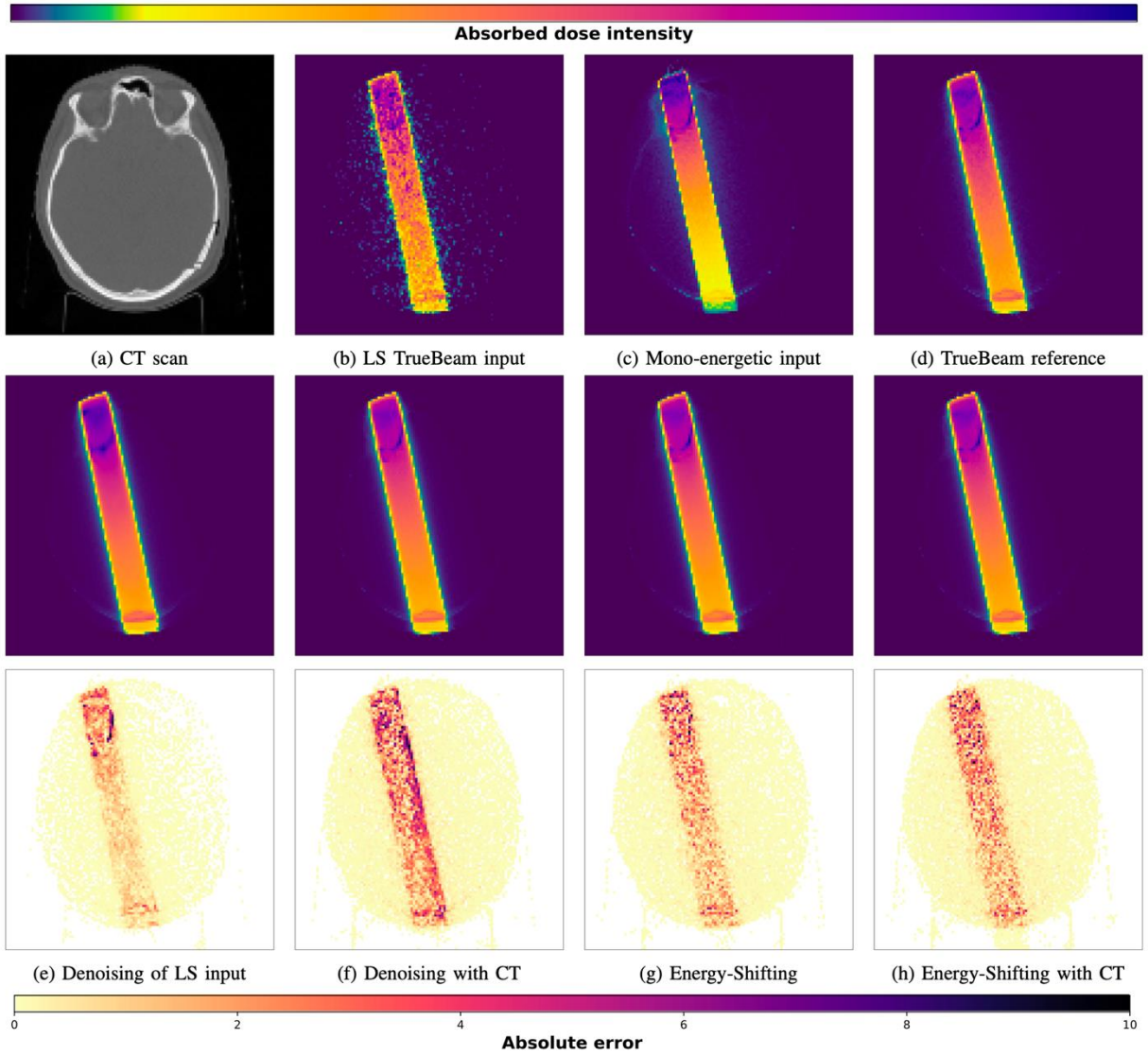
- **Fast** Monte Carlo simulation
- Easy to simulate **MLC**
- GPU acceleration
- Only **photon** processes (500 keV)
- Variance Reduction Technique (<1 MeV)

- 150 CT scans (head, pelvis)
- 1 000 samples
- 165 M parameters

Pham et al. 2026
Under review IEEE TRPMS
http://arxiv.org/abs/2604.09157

Results: trained / tested on head dataset

Denoising vs Energy-shifting



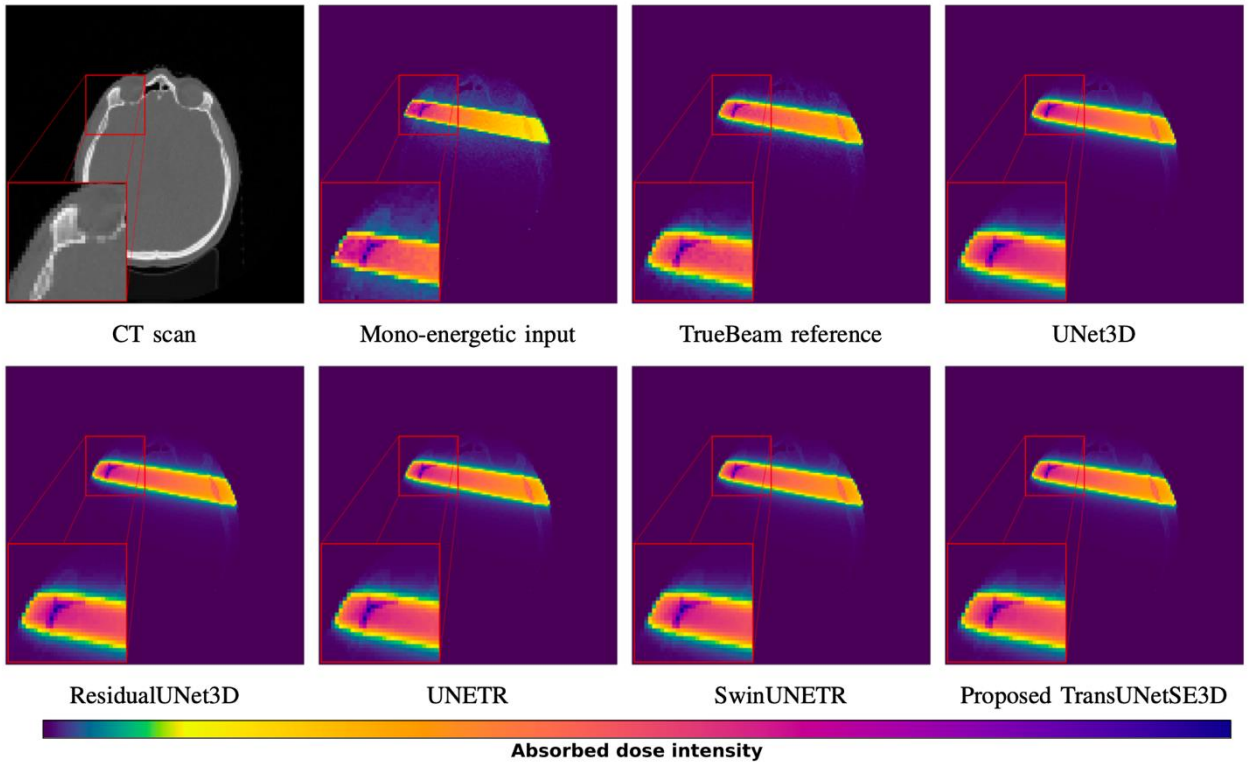
Learning approachs	Training set : Head Input types	Testing set Head	 Pelvis
Denoising	Low-sampling TrueBeam	52.83	49.64
	Low-sampling TrueBeam, CT	56.43	46.33
Energy-Shifting	Mono beam	56.68	48.63
	Mono beam, CT	**57.84**	**50.51**

PSNR

Training set : Head Loss function	Testing set Head	 Pelvis
Mean squared error (MSE)	57.44	48.71
Mean absolute error (MAE)	**57.84**	**50.51**

Results: trained / tested on head dataset

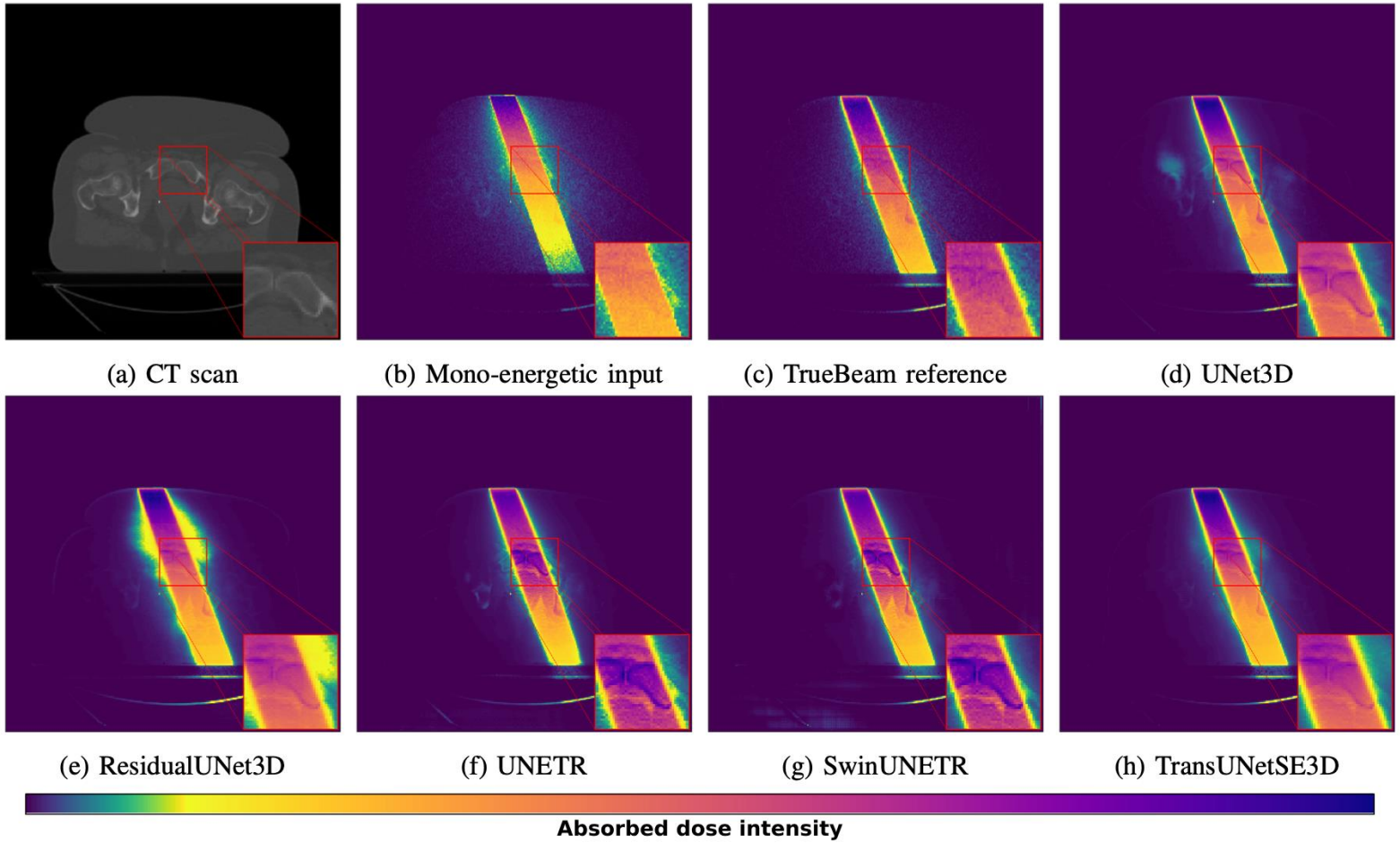
Different architectures



Training set : Head	Testing set	
Architectures	Head	
	PSNR↑	GPR↑
Mono-energetic input	33.91	24.1588
UNet3D	57.84	99.0762
ResidualUNet3D	57.94	99.3584
UNETR	58.11	99.3597
SwinUNETR	58.29	99.3171
TransUNetSE3D	**58.86**	**99.6112**

Results: trained on head dataset / tested on pelvis

Different architectures



(a) CT scan (b) Mono-energetic input (c) TrueBeam reference (d) UNet3D

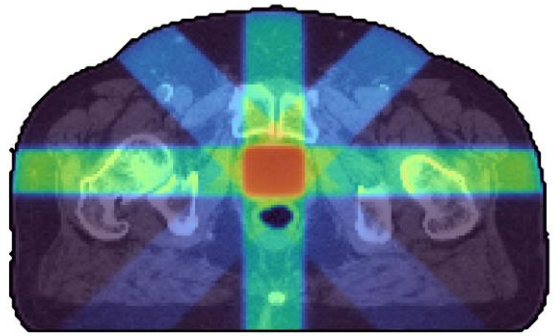
(e) ResidualUNet3D (f) UNETR (g) SwinUNETR (h) TransUNetSE3D

Training set : Head	Testing set			
Architectures	Head		Pelvis	
	PSNR↑	GPR↑	PSNR↑	GPR↑
Mono-energetic input	33.91	24.1588	34.95	16.4977
UNet3D	57.84	99.0762	50.51	74.8951
ResidualUNet3D	57.94	99.3584	51.78	84.8667
UNETR	58.11	99.3597	50.02	75.9518
SwinUNETR	58.29	99.3171	49.02	77.1031
TransUNetSE3D	**58.86**	**99.6112**	**52.45**	**86.7495**

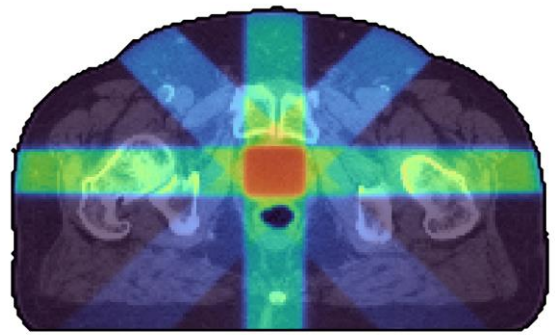
Architectures	Parameters	[Mb] Model size	[s] Exec. time
UNet3D	65.86 M	251.233	10.9816
ResidualUNet3D	113.72 M	433.821	10.8076
UNETR	160.03 M	610.472	12.7666
SwinUNETR	113.57 M	440.422	19.6291
TransUNetSE3D	165.75 M	632.282	13.1340

Simple Application-Based Validation Study

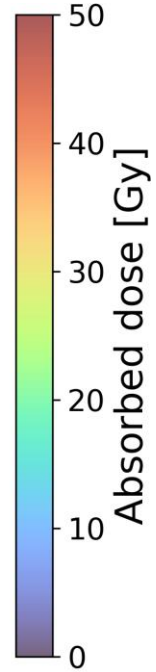
- **Prostate cancer**
  - 6 beams (6 MV TrueBeam Novalis STX)
  - PTV = prostate whole gland
    - Energy Shifting vs Full Monte Carlo
    - GATE10
    - $2x10^9$ particles per beam
    - GGEMS
    - $2x10^7$ particles per beam

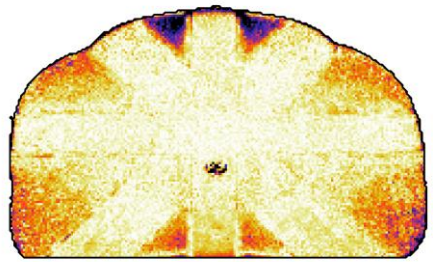


Energy Shifting

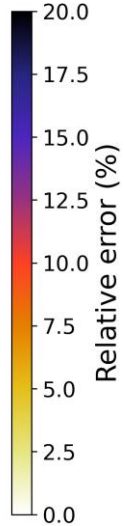


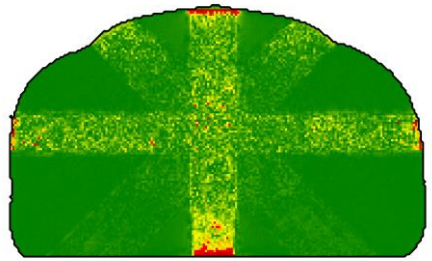
Full Monte Carlo simulation





PTV mean rel. error:
0.6 % ± 0.47 %

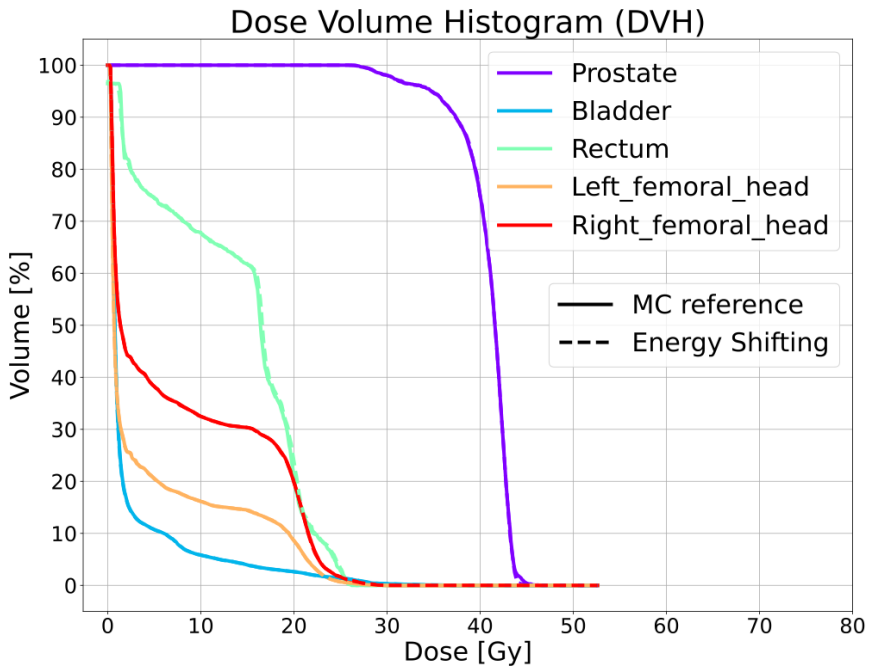




Gamma passing rate
2%/2mm: **99.16 %**



Simple Application-Based Validation Study



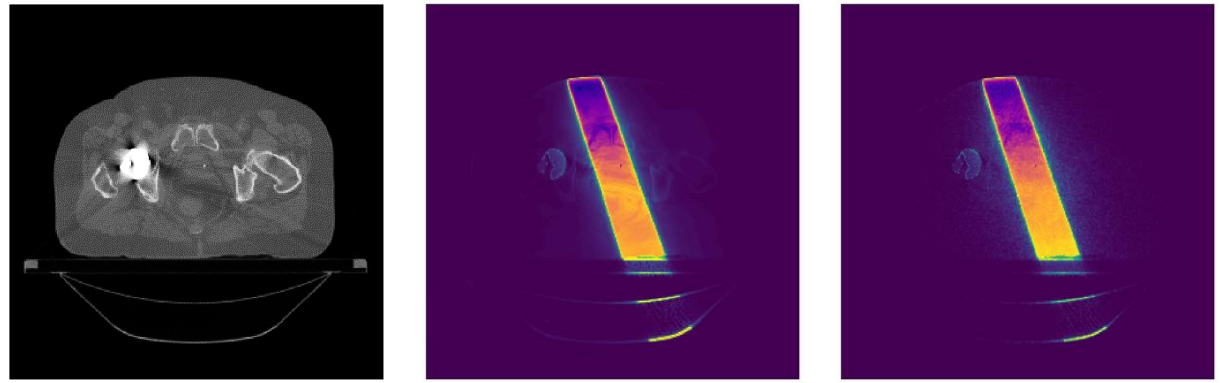
OARs	Mean dose (Gy) ± standard deviation	
	Energy-Shifting	Monte Carlo reference
Prostate	40.8245 ± 3.1708	40.8380 ± 3.1641
Rectum	13.7212 ± 8.0357	13.6158 ± 7.9370
Bladder	2.3429 ± 4.8029	2.3644 ± 4.7858
Left femoral head	4.1969 ± 7.1156	4.2091 ± 7.1079
Right femoral head	7.6668 ± 9.0723	7.6809 ± 9.0744

< 1 %

Calculation time (NVIDIA RTX 4000)

- **Energy Shifting** **90 s**
  - GGEMS 4 s / beam
  - TransNetSE3D 11 s / beam
- **Full Monte Carlo** **200 hours**
  - 10^9 photons
  - Stat. uncer.: OAR ~2% ; PTV ~0.5% ; Avg ~5%

Reliable on unseen data: hip prothesis



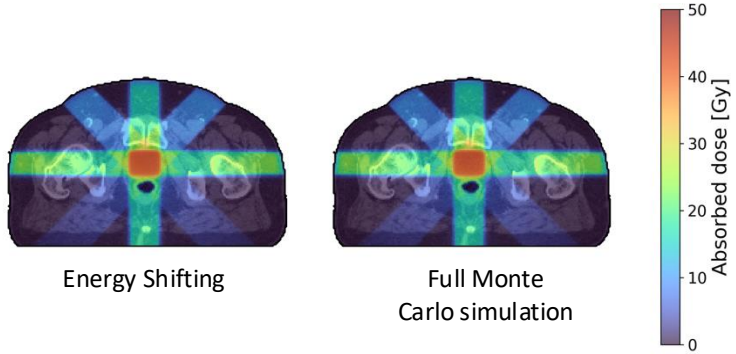
Energy shifting

Monte-Carlo (Gate)

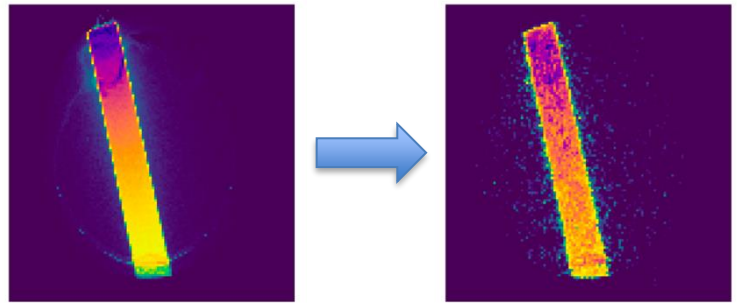
Conclusion

Dose calculation using hybrid approach (MC/DL)
- Reliable
- Accurate
- Fast, but sill not enough

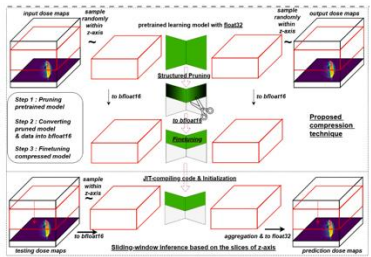
  - **Energy Shifting** **90 s**
    - GGEMS 4 s / beam
    - TransNetSE3D 11 s / beam



Perspectives
- GGEMS: decrease nb of particles ($2x10^7$ photons)



- TransNetSE3D: compression



A Fast and Generic Energy-Shifting Transformer for Hybrid Monte Carlo Radiotherapy Dose Calculation

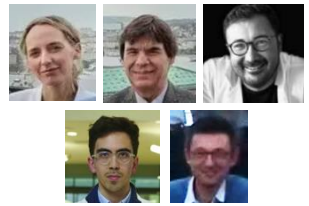
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Brest

ACTION Team : *Multimodal Imaging Guided Therapeutic Action in Oncology*



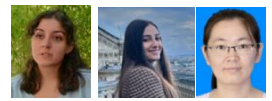
Faculties



Med. staff (Brest University Hospital):



Research engineers





Students