# ESTIMATING OUT-OF-FIELD DOSE DISTRIBUTION BASED ON MONTE CARLO TRAINING DATASET

Maxime Jacquet CREATIS Lyon

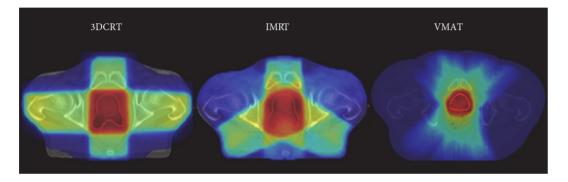








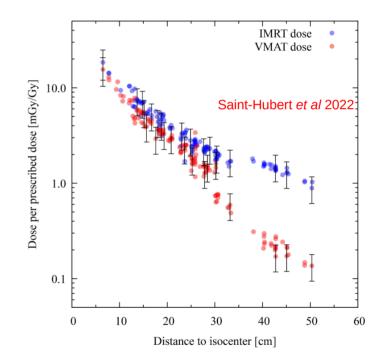
### **Out-Of-Field dose**



Comparison of the deposited dose according to treatment modality Vanneste *et al* 2016

Recent photon radiotherapy methods:

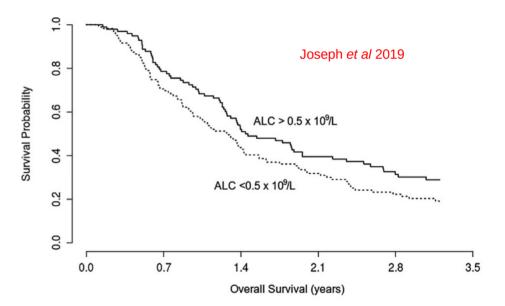
- Diminution of the high dose deposited outside of the tumour volume
- Higher peripherical dose deposited



Experimental measurements of Out-Of-Field dose for IMRT and VMAT in an anthropormorphic phantom

### **Out-Of-Field dose**

- Out-Of-Field (OOF) dose consequences:
  - Increased risk of radiation-induced cancers
  - Lymphopenia: negative correlation with patient overall survival
- Immuno-radiotherapy implementation
  - Precise estimation of OOF dose
  - ⇒New dose constraints on lymphocyte-rich structures (thymus, bone marrow, spleen ...)

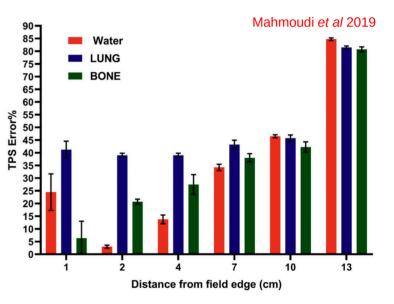


Overall survival with post-treatment absolute lymphocyte count (ALC)

### **OOF** dose estimation

- OOF dose = below 5 % isodose
- Treatment Planning systems (TPS) strongly underestimates the deposited dose
- To accurately estimate OOF dose:
  - Analytical models
  - Monte-Carlo (MC) simulations

	Analytical models	MC simulations	
Calculation time	++ - ~ minutes ~ days		
Accelerator design	++ Simple models	- Accurate models	
Precision	+	++	
Empirical adjustement	- Derive parameters from experiments	++ Matching experiments	
Adaptability	-	+	



Difference between dose measurements and Monaco TPS predictions Lymphocyte-Sparing Artificial Intelligence-guided Radio-Immunotherapy (LySAIRI) RHU project

Collaboration:

- CLB (Centre Léon Bérard)
- CREATIS
- IGR (Institut Gustave Roussy)

CREATIS



Deliver novel solutions toward the first effective implementation of immuno-radiotherapy

 Deep learning tools to quantify the OOF dose

# OOF dose estimation

#### Deep learning models trained by MC simulations

	Analytical models	MC simulations	Deep learning models
Calculation time	++ ~ minutes	- ~ weeks	++
Accelerator design	++ Simple models	- Accurate models	-
Precision	+	++	+(+)
Empirical adjustement	- Derive parameters from experiments	++ Matching experiments	++
Adaptability	-	+	++

# **Training datasets**

Proof of concept:

- Images of patients with a head and neck cancers
- Dataset training: pair of corresponding dose distributions
  - TPS calculations (Monaco)
  - MC simulations of an Elekta versa HD: GATE

⇒Generation of the OOF dose directly from the TPS information

### GEANT4 wrapping:

- Easy access to GEANT4 functionnalities
- Additionnal features
- Collaborative development

#### Medical physics applications

#### **Dosimetry studies**

- External and internal therapy
- Hadrontherapy

Imaging systems

- PET
- SPECT
- Compton camera
- X-ray

### However:

- Old code
- 15 years of development

Hundreds of contributors

- Maintenance issues

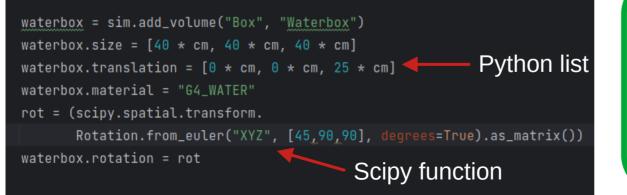


GATE

New release of Gate: **GATE 10** 

# GATE 10

- Based on new C++ technologies
- Python wrapping:
  - Easy to use
  - Combination with numpy/scipy libraries
- Open access collaborative work



Windows compatibility

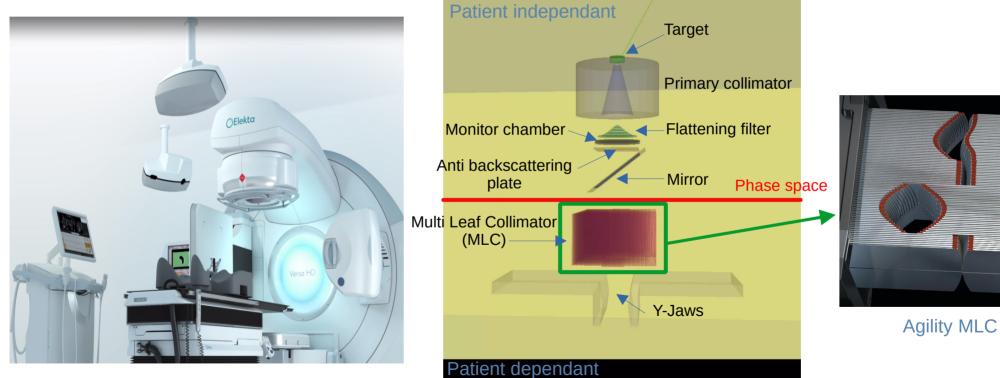
# Multithreading available

#### • Still in development

 Beta version available at the end of the year

Waiting for your contributions

### Simulation of the Elekta Versa HD



Elekta Versa HD

#### Elekta LINAC VERSA HD 6 MV simulated with GATE 10

### Estimation of OOF calculation times

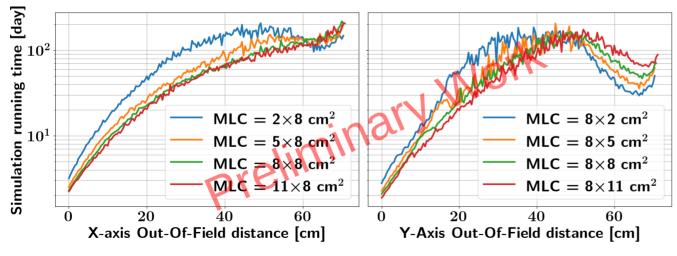
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Simulation settings

- Phase Space

- Ideal MLC

- Targeted error on OOF dose distribution: 5 %
- Number of photon to simulate
- Simulation running time on a voxelized image



Day number to achieve 5 % of statistical uncertainties as a function of the axis-distance for differents MLC apertures

### Estimation of OOF calculation times

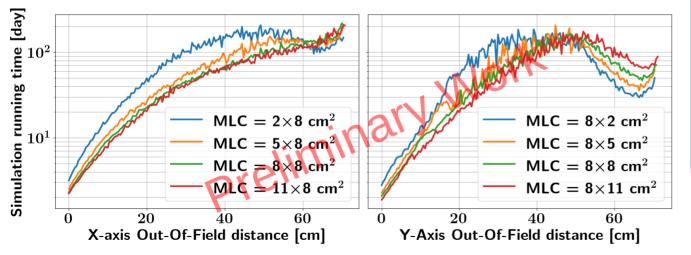
Simulation settings

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- Ideal MLC



- Number of photon to simulate
- Simulation running time on a voxelized image



For far OOF (~40 cm):

- $\sim 10^{11}$  photons to simulate
- 50 200 simulation days on one thread (i9-13950HX)

If targeted precision = 1 %

Running time ~ 25 times higher

MC simulations acceleration

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Day number to achieve 5 % of statistical uncertainties as a function of the axis-distance for differents MLC apertures

### Perspective: strategies for MC simulation acceleration

Particle generation

#### Virtual Source Model approach

- Several virtual sources:
  - Primary photons
  - Secondary photons Chetty et al 2000 Chabert et al 2016
- Faster but less precise

« Full » MC approach

- Precise but time consuming

Phase space before the MLC

#### Generative Adversarial Network (GAN) approach

- Particle generation with GAN
  - Trained on phase space data
- Faster but precision on low dose ?

Sarrut et al 2019

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#### Sarrut et al 2019

#### Particle transportation

#### Biasing approach:

- Most of OOF events: Compton scattering
  - « Smart » suppresion of p.e. processes
  - Weighting by the event probability of occurence

Variance reduction but edge-effect ?

#### Selective Tracking Lenght Estimator (TLE) approach

- « Low » energy photons in the OOF regions:
  - Local photon energy deposition
- Variance reduction but realistic approximation ?

Smekens et al 2012

# CONCLUSION

#### LySAIRI project:

- Deep learning models development
- Accurate MC datasets training

**Development of MC simulations** 

- Elekta Versa HD in GATE 10
- Running time estimation for one image:
  - 50 200 days on one thread
  - Daily scale with the cc-in2p3

Acceleration strategies of MC simulations