Optimized Reconstruction of the Position of Interaction in High-Performances γ-Cameras

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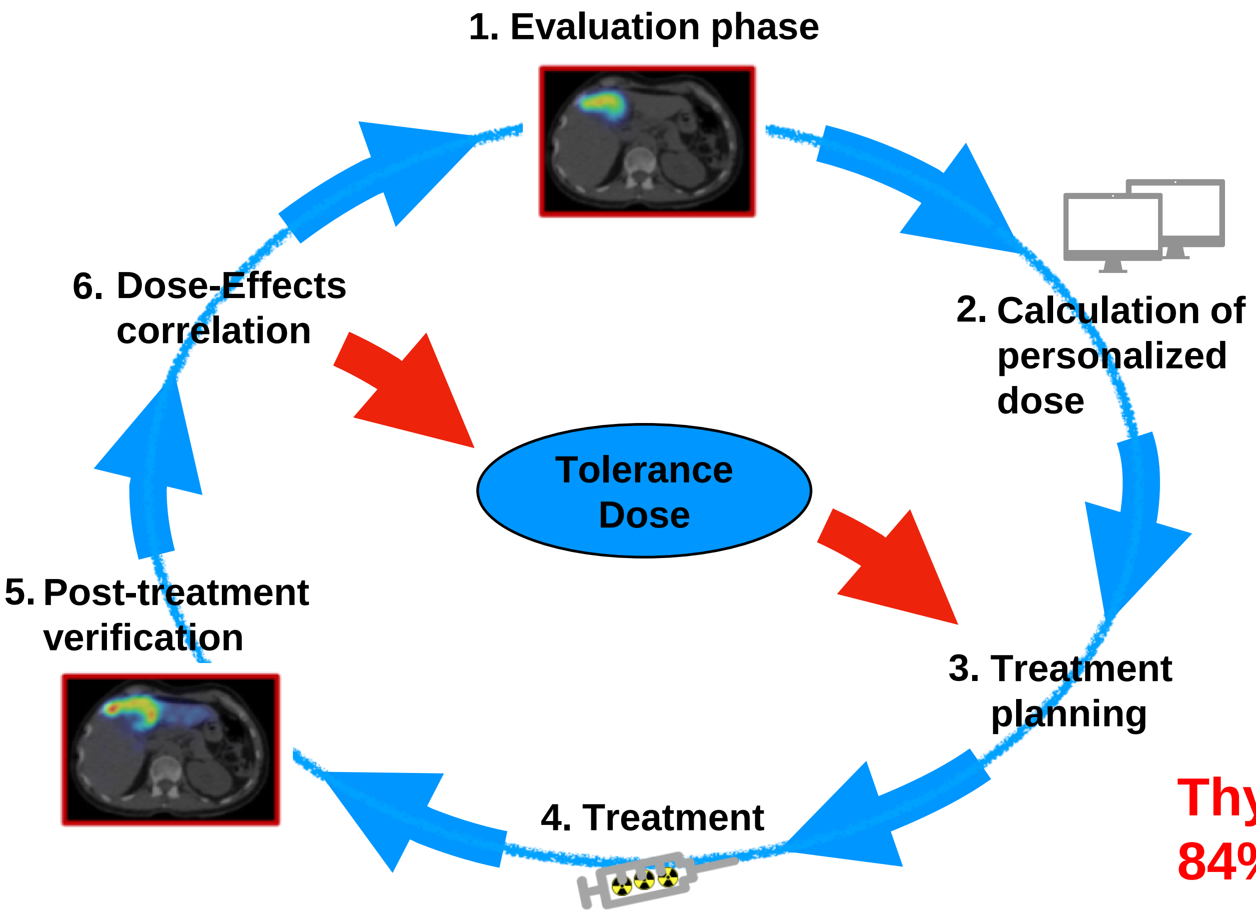
Role of dosimetry in internal radiotherapy



Dose-based treatment planning : determine the activity to be injected according to the desired clinical outcomes and tolerance doses of organs at risk

Post-treatment verification : control that the absorbed dose corresponds to the one estimated from the evaluation phase

Correlation between the dose released to the tumors/organs at risk and the clinical effects

Thyroid diseases treatments with ^{131}I: 84% of all MRT treatments !

Challenges and constraints of dosimetry for MRT

Improve the individual quantitative assessment of the heterogeneous distribution and biokinetics of ^{131}I before and after treatment administration for thyroid diseases

Development of a high-resolution mobile camera, 10x10cm^2 Field of View, for imaging with high energy gamma rays (>300 keV) **and high photon fluence rates** (200 kcps @ 364 keV)

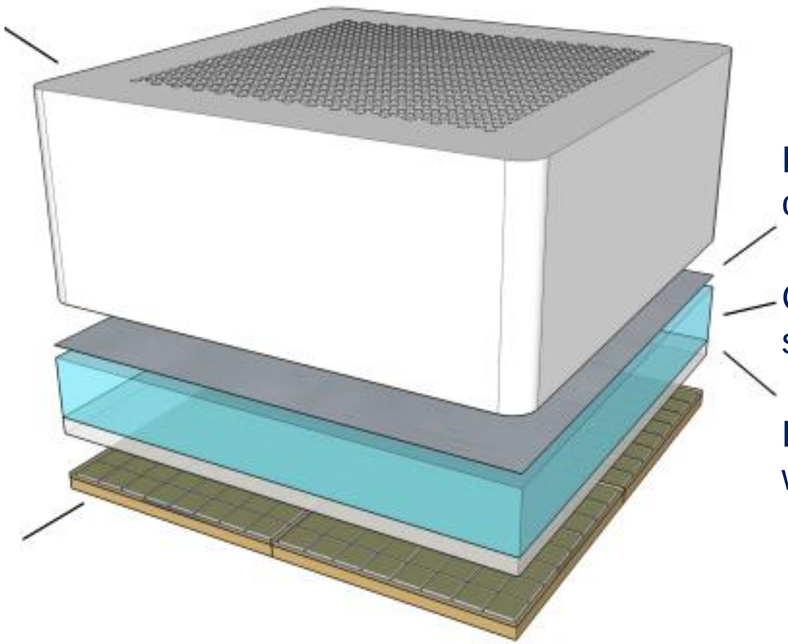
Mobility to perform exams at the patient's bedside or in an isolated room for an accurate temporal sampling of the ^{131}I biokinetics

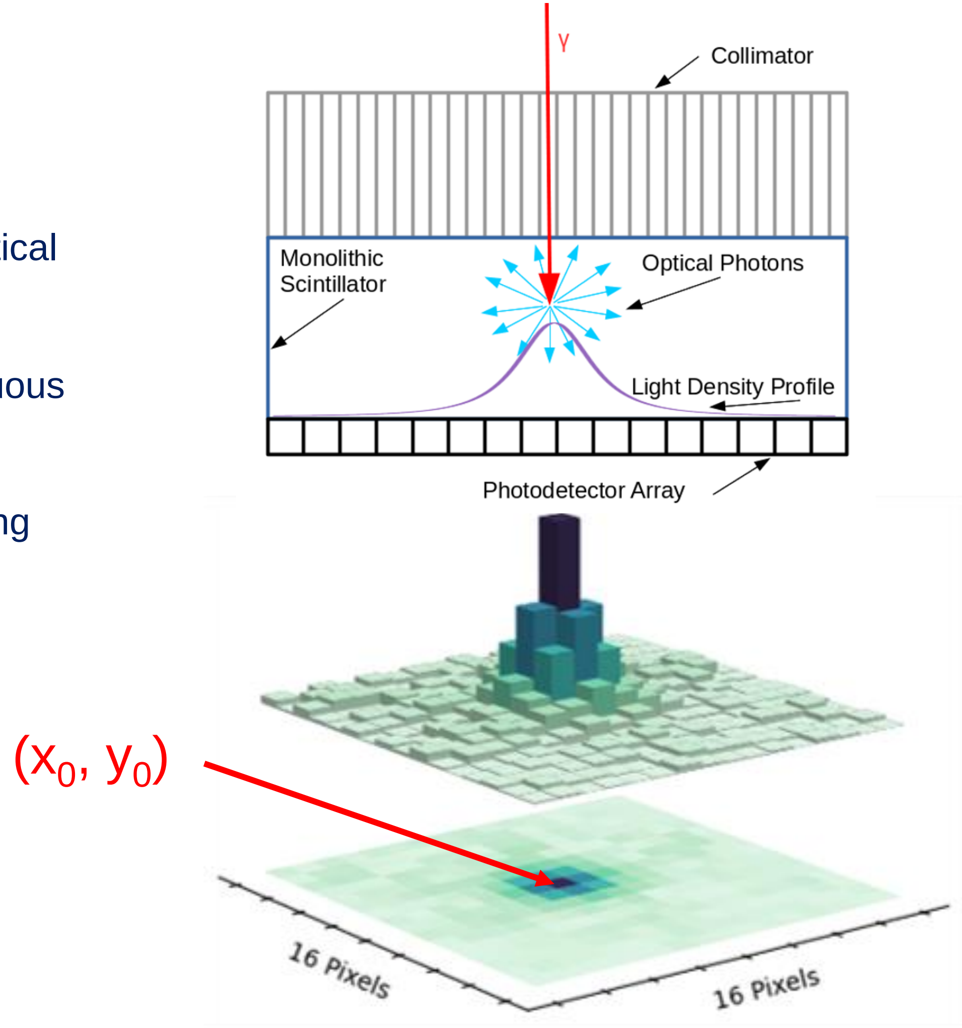
Compactness to improve image contrast (reduced camera/source distance and optimized angular view)

High spatial resolution (3 to 6 mm FWHM) to improve detectability and quantification of small activity heterogeneities (reduction of the partial volume effect)

High energy resolution (<8% FWHM @ 364 keV) to reduce scatter from high energy gamma rays

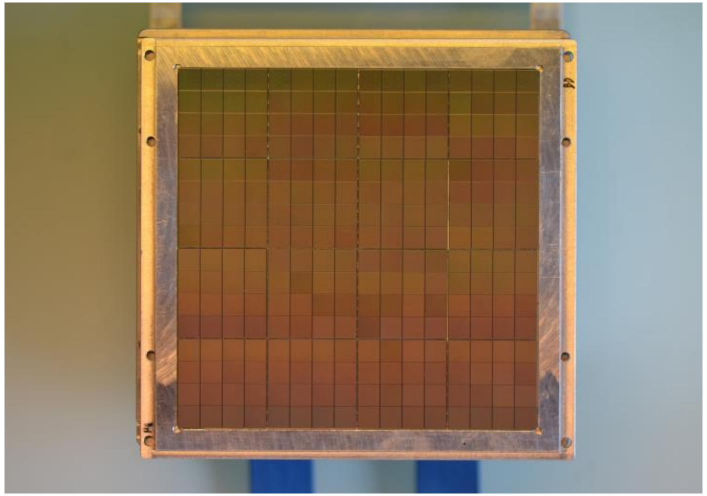
Design of the miniaturized gamma camera

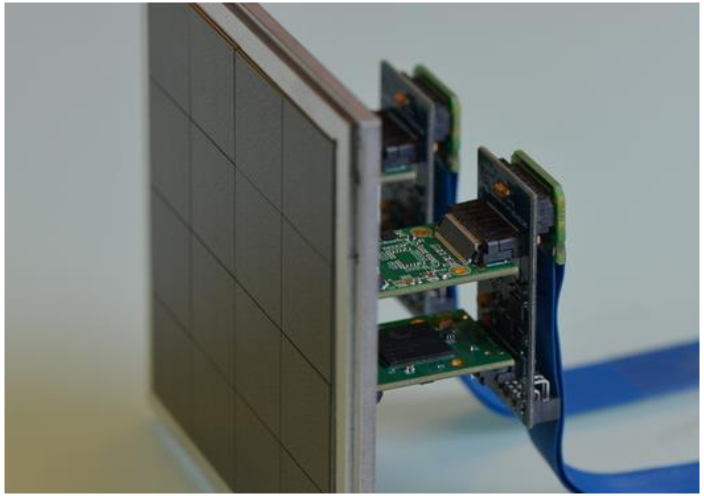


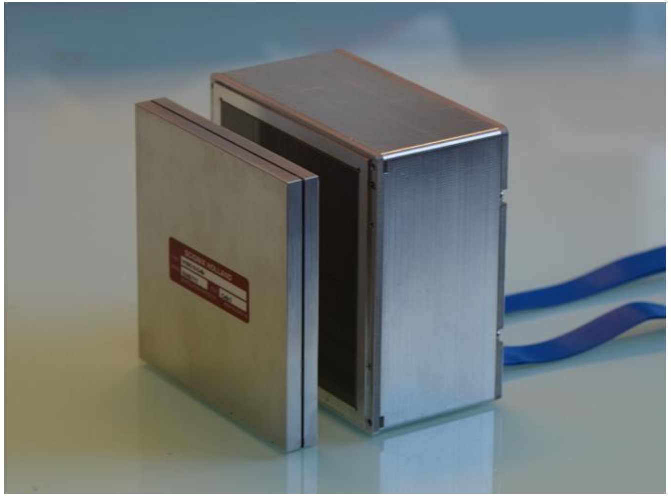


- Overall dimensions : 18x18x20 cm^3
- Total weight : 50 kg (including 30 kg lead shielding and 9 kg collimator)

10x10cm^2 Field of View clinical prototype

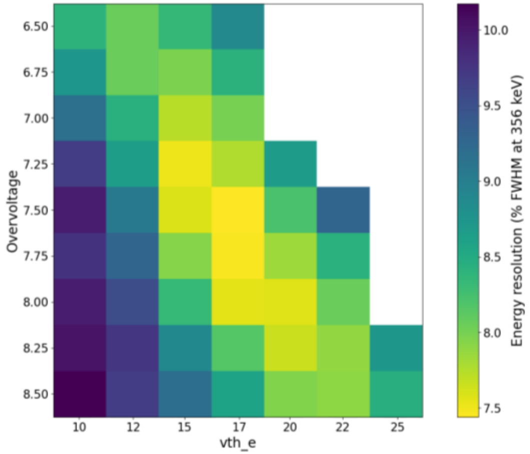






- The photodetection system
  - 256 Hamamatsu S13361-6050NE-04 monolithic arrays (6x6 mm^2/50µm) mounted on an interface PCB (Sixteen 4x4 arrays)
  - 10x10cm^2 and 1 cm thick $CeBr_3$ continuous scintillator with reflective coated edges
  - Commercial acquisition electronics (TOFPET 2B ASICs - PETSys Electronics)
  - Spatial coincidence trigger to reject dark counts
  - Acquisition dead time < 1% at 150 kevents/s

Instrinsic performance



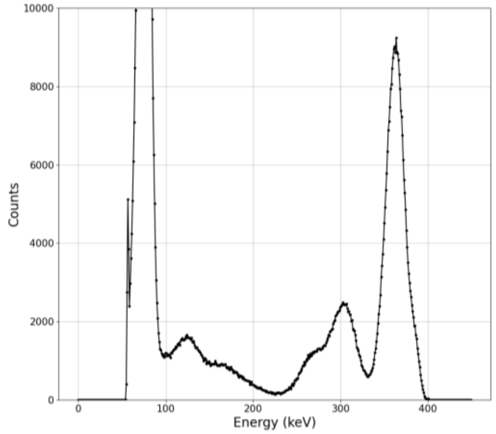
Energy resolution vs electronics parameters

Spectroscopic performance evaluation :

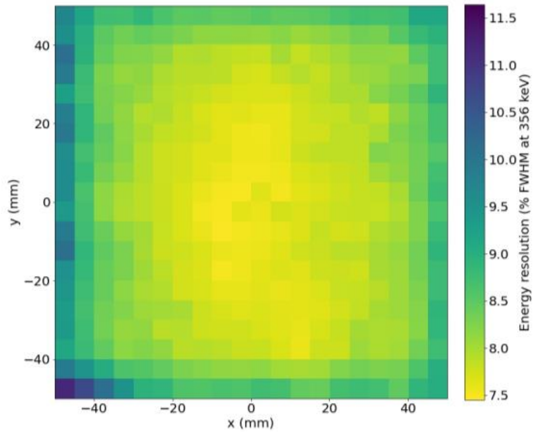
- Climatic chamber at 21°C
- Collimated ^{133}Ba source (356 keV) mounted on a 3D motorized platform
- Optimal set of electronics parameters:
- ER = 8.06±0.21% in CFOV (75% of full FoV)

Spatial performance evaluation :

Spatial resolution



133-Ba spectrum (Central FoV)



Energy resolution map

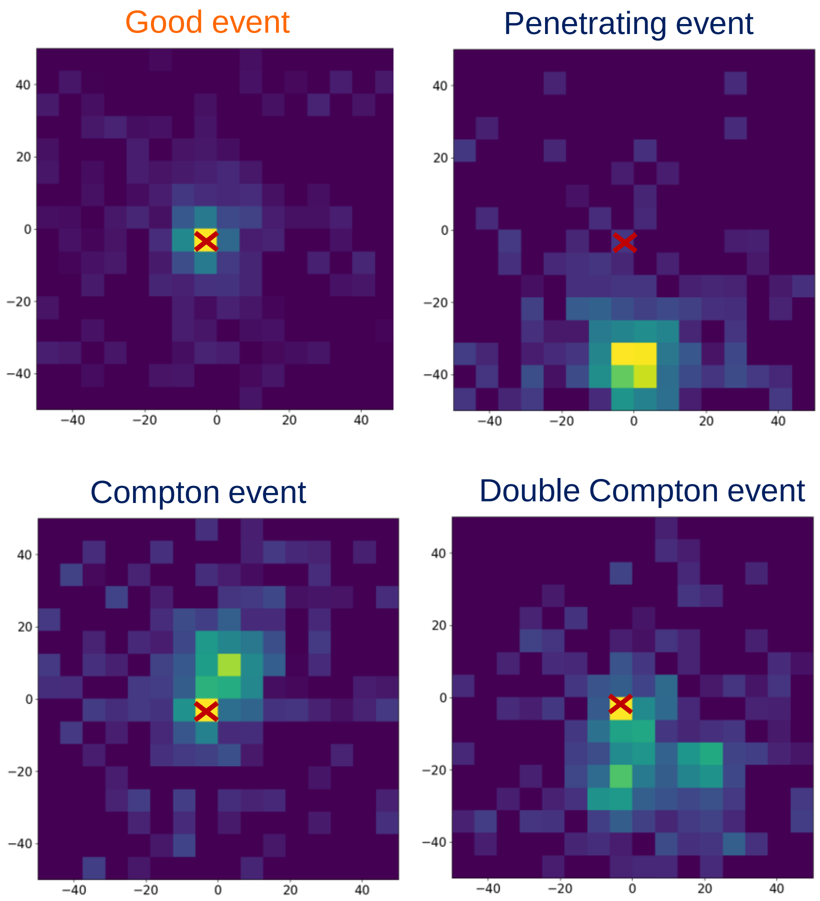
Reconstruction Methods

Method	Type	Speed	Ref. data free	Performances	Comments
Centroid [1]	Geometric	+ +	+	−	Strong distortions, no DoI
Analytic model fit [2]	Iterative	+	+	−	Optical properties dependent
Interpolated model fit [3]	Iterative	−	−	+	No easy DoI
K-Nearest Neighbors [4]	Machine Learning	− −	−	+	Computing intensive
Neural Network [5]	Machine Learning	+ +	−	+	Many parameters to tune

[1] R. Pani et al., IEEE Nuclear Science Symposium Conference Record, 2011, pp. 3395-3398
[2] C. Trigila et al 2022 Phys. Med. Biol. 67 035011
[3] A Morozov et al 2017 Phys. Med. Biol. 62 3619
[4] H. T. van Dam et al., IEEE Transactions on Nuclear Science, vol. 58, no. 5, pp. 2139-2147, Oct. 2011
[5] Gangadhar Jaliparthi et al 2021 Phys. Med. Biol. 66 145008

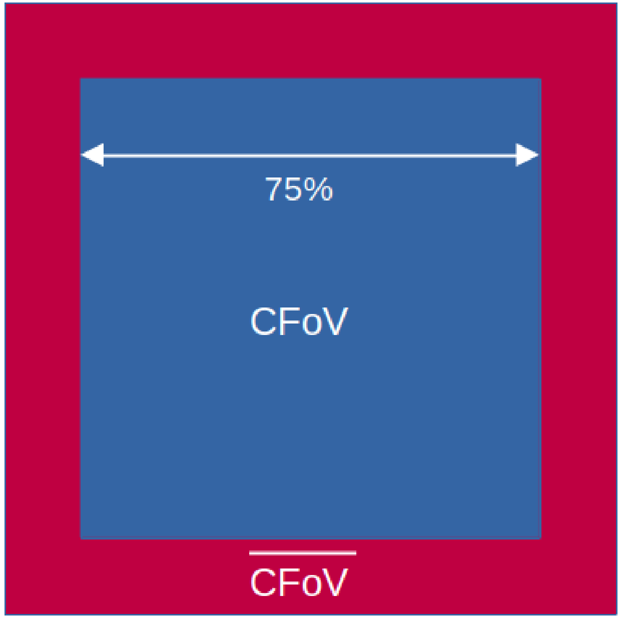
2 Data sets

- Scan:
  - ^{133}Ba source (356 keV) with 0.5 mm diameter single-hole Tungsten collimator.
  - Scan over the whole FoV with 1 mm step
  - Spurious events filtering : ~2k full-energy evts/position
  - 2 frames subsets:
    - ~1000 full-energy peak evts/position for reference/training
    - ~1000 full-energy peak evts/position for validation
- Flood field:
  - ~ 30.10^6 full-energy peak events
  - Non-collimated ^{133}Ba source set at ~50 cm



Spatial Performance Measurement

- Regions:
  - Central Field of View (CFoV) = 75% (lin) of the total FoV.
  - Complementary Central FIeld of View (/CFoV).

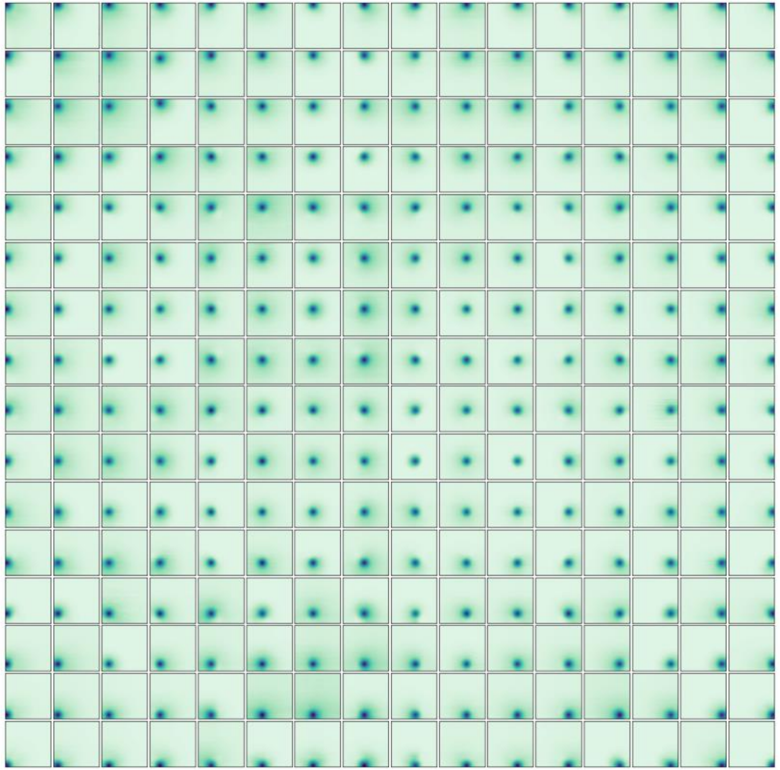


- 4 Types of measurements for each region [*]:
  - Scan based:
    - Spatial Resolution (SR): Average of the SR at each scan position.
    - Local Intrinsic Spatial Distortion (LISD): Average of the distance between the measured scan position to their row and column linear regression values.
  - Flood Field based
    - Integral Uniformity (IU): Ratio between standard deviation and mean of the flood field, reconstructed, smoothed image.
    - Differential Uniformity (DU): mean of the local variation of the IU (based for each pixel on the 2, 4, 6, 8 and 10 closest pixels in both row and column directions)

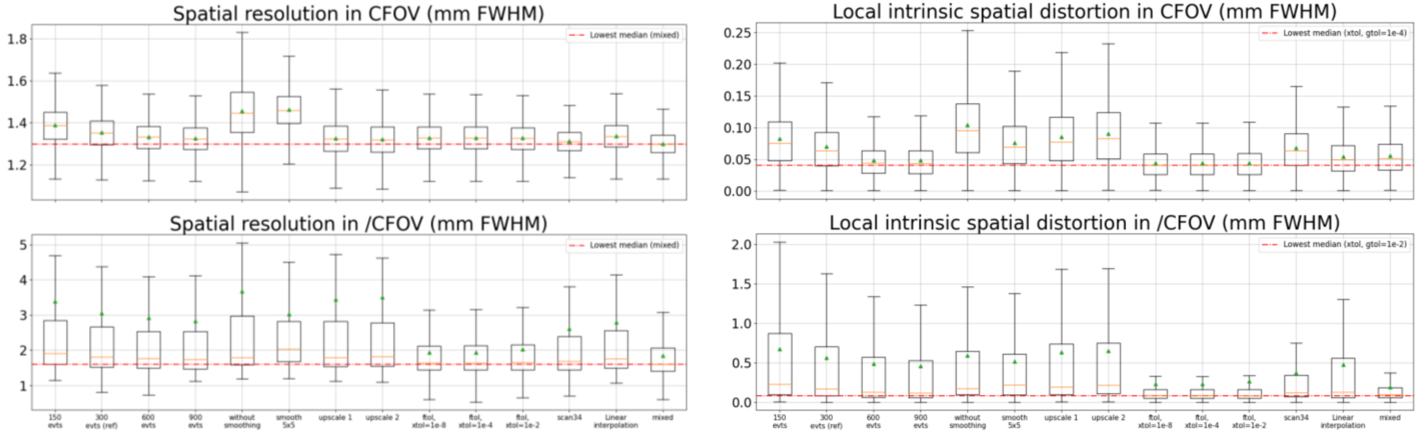
*B.S. Bhatia et al. Physica Medica 31 (2015) 98e103

Interpolated Model Fit

16x16 pixel response functions

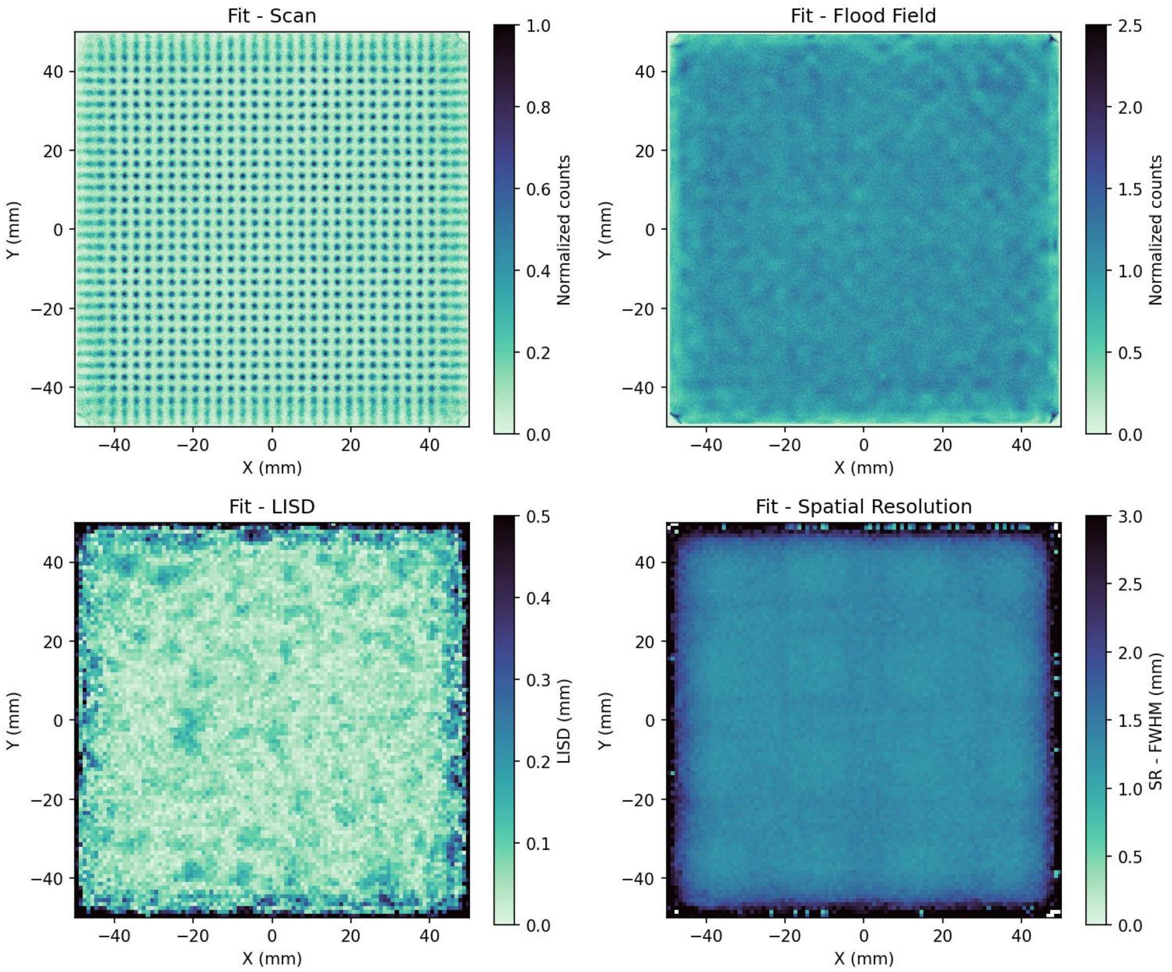


- The Reference data set can be used to determine each SiPM discrete response function by averaging of N=300-600 frames
- Values can then be interpolated at any (x, y) position.
- For each frame of the validation data set a fit (non-linear least-square) is performed for best (x_0, y_0) estimation.
- At each iteration a value is interpolated for each pixel.
- Optimization in terms of: evts/ref position, number of ref positions, frame smoothing, fitter optimization, ...



Fit - Results

- Best parameters set:
  - Ref positions: 34x34 (3 mm step)
  - Number of frame per scan position : 600evts
  - Frame smoothing
  - Interpolation type: spline
- Performances
  - SR CFOV: 1.30±0.06
  - SR /CFOV: 1.85±0.77
  - LISD CFOV: 0.06±0.03
  - LISD /CFOV: 0.19±0.37
  - IU CFOV: 4.5%
  - IU /CFOV: 5.76%
  - DU CFOV: 3.66%
  - DU /CFOV: 3.66%



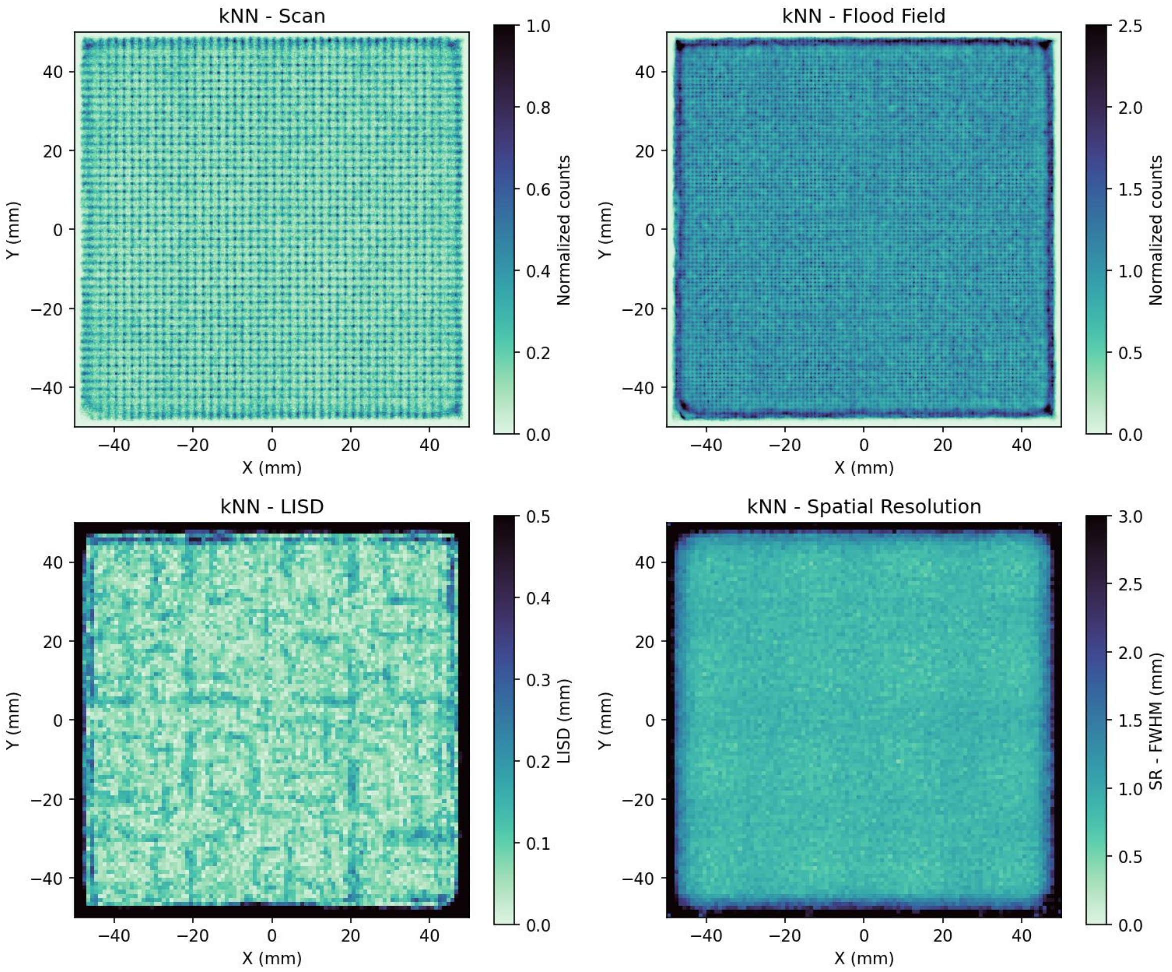
K-Nearest Neighbors

- The k-Nearest Neighbors (kNN) method consist of finding, for each frame, the k closest in terms of pixel to pixel Euclidean distance.
- Regression of the position of each frame is then evaluated from the mechanical position of these k closest distances:
  - Barycenter of the mechanical positions weighted by their inverse Euclidean distance.
  - Fit of the positions with a Lorentz-like bi-variate function

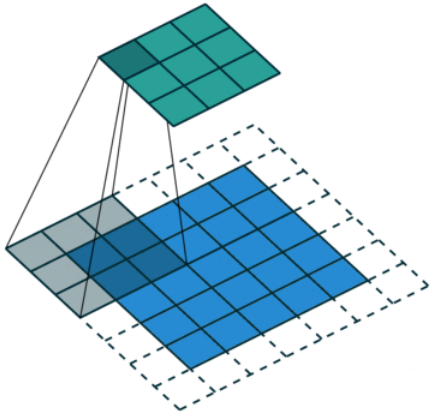
K-NN Results

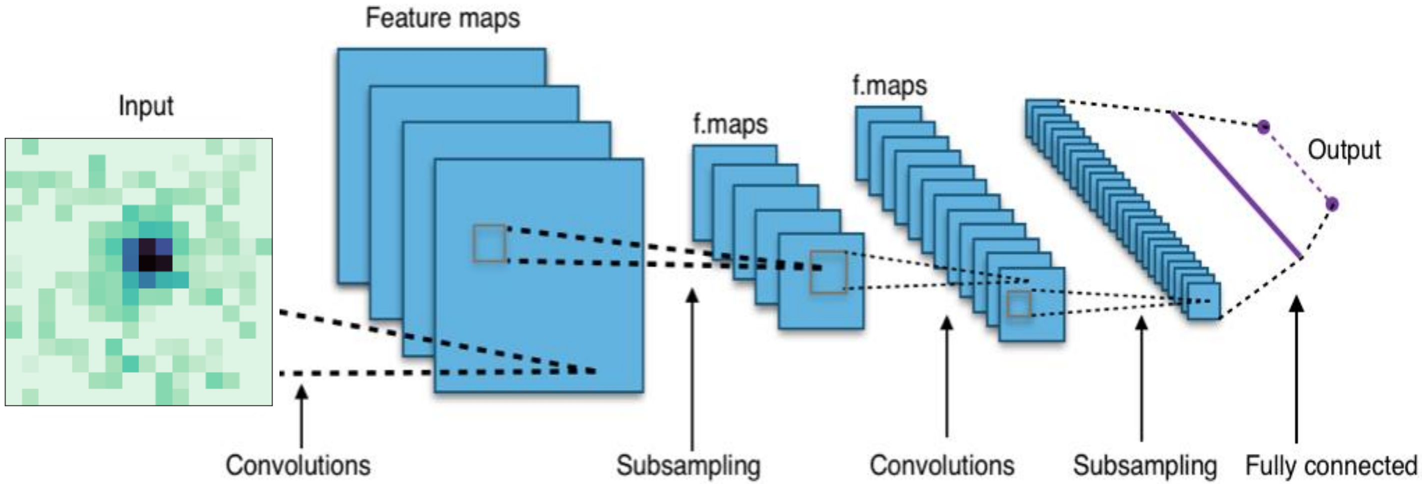
- Parameters:
  - Ref positions: 100x100 (1 mm step)
  - 600 events/scan position
  - 300 Nearest Neighbors
  - Bi-variate Lorentz-like function maximum-likelihood fit

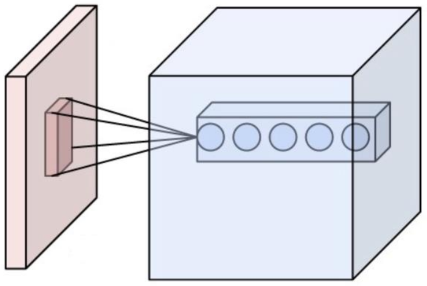
- Performances
  - SR CFOV: 0.83±0.13
  - SR /CFOV: 3.96±184
  - LISD CFOV: 0.01±0.08
  - LISD /CFOV: 0.03±0.78
  - IU CFOV: 3.81%
  - IU /CFOV: 9.92%
  - DU CFOV: 3.29%
  - DU /CFOV: 3.51%



Convolutional Neural Networks



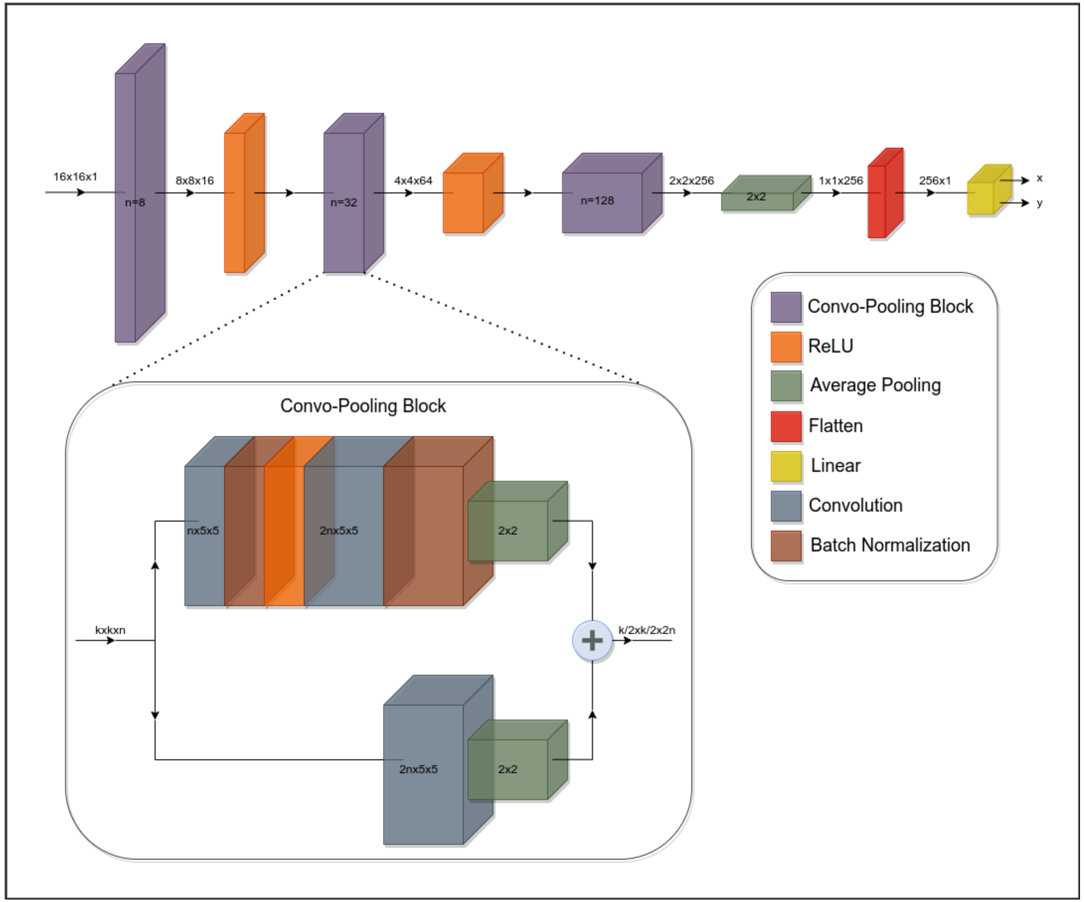


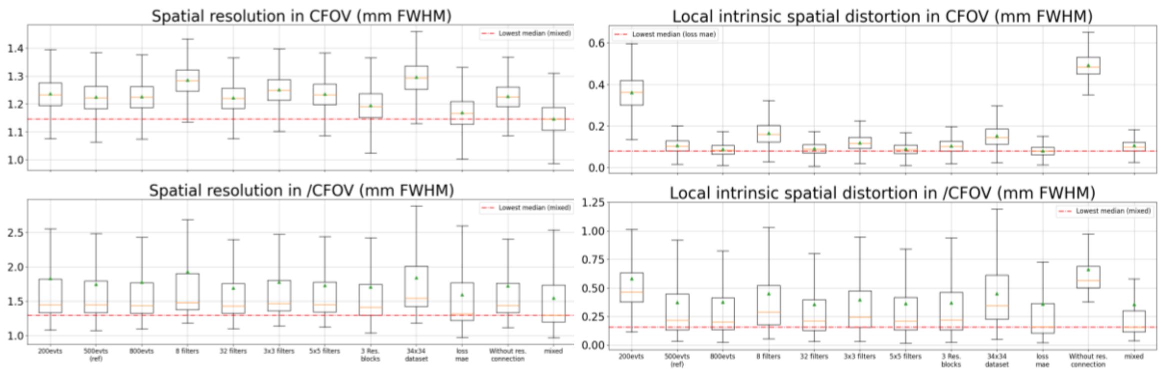


- Convolutional Neural Networks (CNN) use maps obtained by convolution of a kernel on the image.
- At each layers the numbers of feature increases while the dimension of the convolution maps decreases by pooling.
- Goal is to use geometrical features of the input images

Deep Residual Convolutional Neural Network

- Deep Residual Convolutional Neural Network (DR-CNN) use batch normalization to improve training performances
- Skip connections are then used to avoid gradient issues
- DR-CNN are a sequence of small CNN
- Keras + Tensorflow
- Optimized in terms of: Network structure, kernel size, number of filters, loss function, number of training samples and reference scan positions, ...





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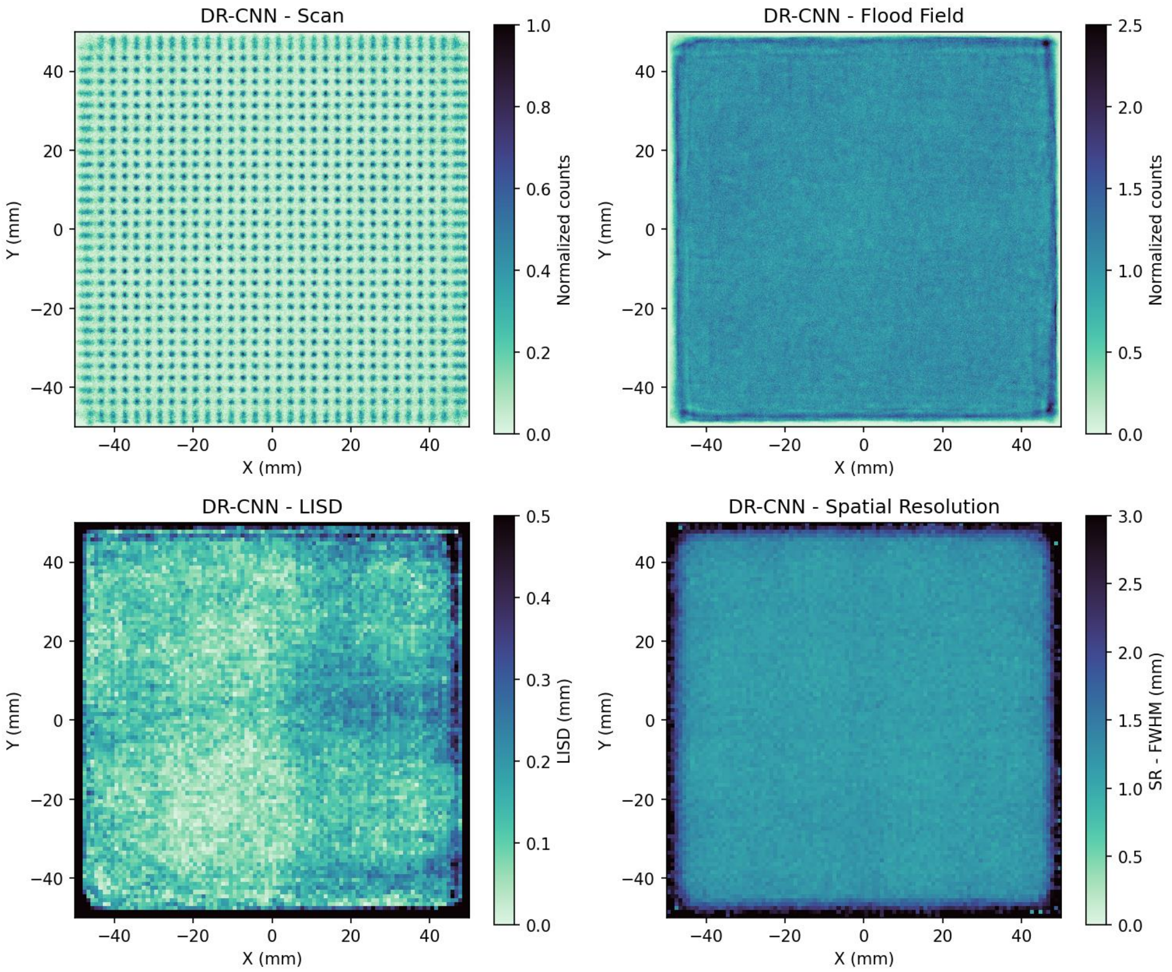
DR-CNN - Results

- Best parameters
  - 30 epochs
  - Ref positions: 800 evts/pos, 1 mm step
  - 3 Residual blocks (=6 conv. Layers)
  - Around 1 M neurons
  - Loss function: MAE
- Performances
  - SR CFOV: 1.15±0.06
  - SR /CFOV: 1.54±0.55
  - LISD CFOV: 0.11±0.05
  - LISD /CFOV: 0.35±0.66
  - IU CFOV: 3.35%
  - IU /CFOV: 4.35%
  - DU CFOV: 2.39%
  - DU /CFOV: 2.45%



Summary

	SR CFOV	SR /CFOV	LISD CFOV	LISD /CFOV	IU CFOV	IU /CFOV	DU CFOV	DU /CFOV	Speed
Fit	1.30±0.06	1.85±0.77	0.06±0.03	0.19±0.37	4.5%	5.76%	3.66%	3.66%	~100 evt/s/CPU
K-NN	0.83±0.13	3.96±184	0.01±0.08	0.03±0.78	3.81%	9.92%	3.29%	3.51%	< 1 evt/s/CPU
DR-CNN	1.15±0.06	1.54±0.55	0.11±0.05	0.35±0.66	3.35%	4.35%	2.39%	2.45%	~5000 evts/s (GPU) ~2700 evts/s (native multi-cpu)

- All three methods yield spatial performances sufficient for our camera, but:
  - k-NN has good spatial resolution but is too slow for our semi-real time needs
  - Interpolated fit overall good but doesn't outperform on any criteria
  - DR-CNN give very good uniformity values and provides overall good performances while being much faster

→ Deep Residual Convolutional Neural Network is our choice

Acknowledgments

IRSN – Institut de Radioprotection et de Sûreté Nucléaire

Tiffany Beaumont
David Broggio
Mohamed Bensiali
Estelle Davesnes
Aurélie Desbrée

IJCLab – Irène Joliot-Curie

Carlotta Trigila
Yves Charon
Françoise Bouvet
Laurent Ménard
Laurent Pinot
Marc-Antoine Verdier

Denis Reynet
Harald Ramarijaona
Aurélien Blot

Institut Universitaire du Cancer de Toulouse Oncopole

Olivier Caselles
Laviana Vija
Delphine Vallot

Institut Claudius Regaud

Mathieu Sinigaglia
Slimane Zerdoud

Hôpitaux universitaires Paris-Sud (Antoine-Béclère, Bicêtre, Paul-Brousse)

Luis Ammour
Jad Farah
Aurélie Forbes

- With financial support from ITMO Cancer AVIESAN within the framework of the Cancer Plan (AAP Physicancer 2019-2023, THIDOS project)