Neural Networks for Position of Interaction Reconstruction in Monolithic Scintillator for γ-Cameras.

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Gate Technical Meeting

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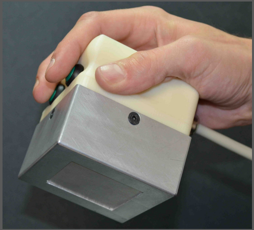
Context

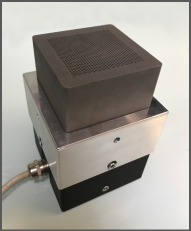
- Compact and mobile high performances γ-cameras show large interest for various new clinical applications

Camera MAGICS/TReCam[1]



- Intraoperative radio-guided surgery for breast cancer (SNOLL)

Camera MoTI[2]

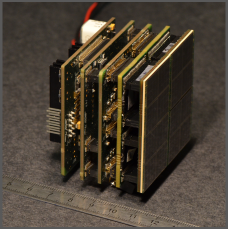
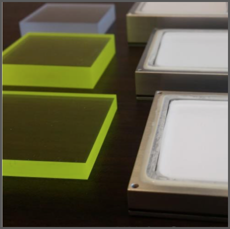
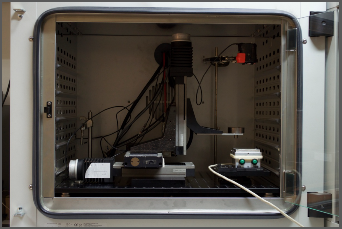


- Individualized thyroid radio-iodine therapy dosimetry

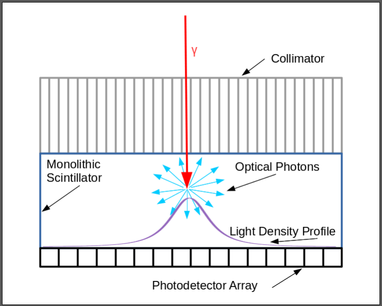
[1] A. Bricou PhD thesis 2018
[2] C. Trigila PhD thesis Sept 2019

γ-Camera @ IMNC

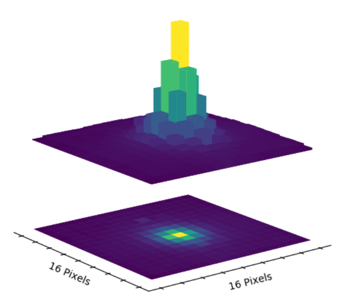
- High performances compact and mobile γ-camera
- Module de photodétection 256 pixels[3]
  - 4 MPPC 8×8 pixels. (3 mm SiPMs)
  - 8 ASICs EASIROC 32 channels with tunable 8 bits DACs
  - Motherboard with FPGA + power supply
  - Power consumption : 2.7 W
- 5×5 cm^2 continuous $LaBr_3$:Ce (5 mm to 2 cm thick)
- Scintillators with absorbing or reflective edge coating
- Submillimetric intrinsic spatial resolution and 7% energy resolution @356 keV
- Source on motorized platform in climatic chamber

Camera Schematic



Light Distribution



- Isotropic emission of optical photons at interaction position.
- 2D profile of surface light density.

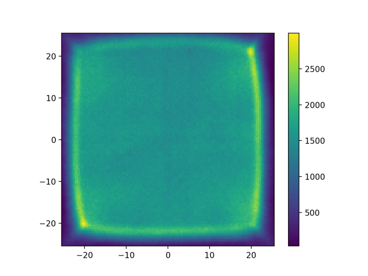
$\Rightarrow$ Reconstruction of position of interaction (x_0, y_0) of γ-rays ?

- γ Events with parameters $\theta = (x_0, y_0, z_0, N_0)$
- Each pixel p_i has the probability to measure N_k photoelectrons (Poisson):

$$\begin{cases} \mathbb{P}_i(N_k|\theta) & = & \dfrac{\mu_i^{N_k}(\theta)e^{-\mu_i(\theta)}}{N_k!} \\ \mu_i(\theta) & \propto & N_0 \times \eta_i(x_0, y_0, z_0) \end{cases}$$

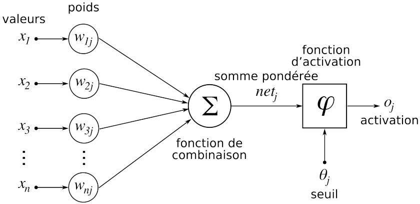
- $\eta_i(x_0, y_0, z_0)$: Pixels light function response: unknown

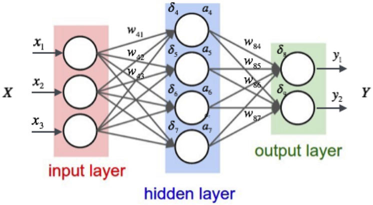
^{133}Ba flood field Reconst. (fit)



Type	Method	Speed	Accuracy	Note
Centroid	Barycenter	✓✓	✗✗	Strong deformation
	Squarred barycenter	✓✓	✗	Strong deformation
Fit	Analytical Model	✓	✓	Hard to model
	Interpolation	✗✗	✓✓	Calibration required
Machine learning	KNN	✗✗	✓✗	Calibration required
	Neural Networks	✓✓	??	Training Required

- Layers of artificial neurons
- Basic Feed Forward network:
  - All neurons are connected to every neurons of the previous and the next layer
  - Each neuron as a weight, a threshold and an activation function (same function for the whole layer)

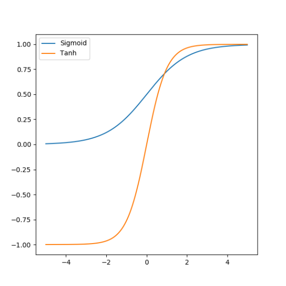




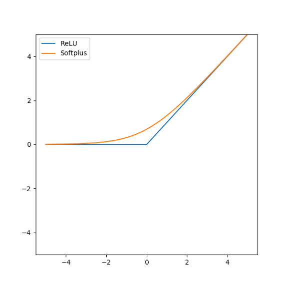
$\Rightarrow$ Output : $o_j = \varphi(\sum_i x_i w_{ij} + \theta_j)$ (or $o_j = \varphi(\mathbf{x}_j \cdot \mathbf{w}_j) + \theta_j$)

- *Sigmoid* : $f(x) = \frac{1}{1+e^{-x}}$
- *Tanh* : $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
- *Linear* (identité) : $f(x) = x$
- *Relu* (Rectified Linear Unit) : $f(x) = max(0, x)$
- *Softplus* : $f(x) = log(1 + e^x)$

Sigmoid, Tanh



Relu, Softplus



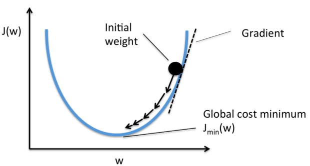
Weights **w** Computation

- Training dataset **X** with known results **y**
- Loss function
  - MSE (Mean Squared Error) : $L = \frac{1}{N}\sum_i(\hat{y}_i - y_i)^2$
  - *etc*

- Retropropagation
  $\Rightarrow$ Blame weights regarding their influence
  $\Rightarrow$ Optimization function
  - Stochastic Gradient Descent
  - Adam[4] (and variations: Adamax, *etc*)

Gradient descent

$$\Delta w_{ij} = -\eta \frac{\partial L}{\partial w_{ij}}$$



$\Rightarrow$ Iterative : Training for several *epoch*

[4] https://arxiv.org/abs/1412.6980v8

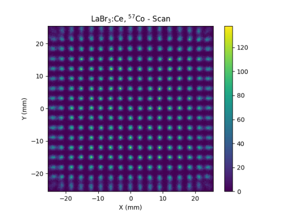
NN Optimization

- Structure
  - Number of hidden layers
  - Nomber of neuron per layer
- What function of activation
  - On each layer
  - Output: linear (regression)
- What loss function: *MSE*
- What optimization method
- What regulizers
- Number of epochs

⇒ Lots of parameters to tune !

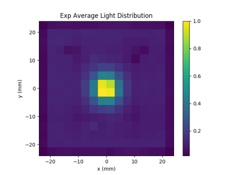
⇒ What training data ?

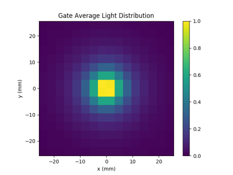
Exp. Scan Collimated ^{57}Co



- Scan with collimated ^{57}Co (ϕ=500 m) with 3 mm step.
- True γ position of interaction: Unknown !
  - Evaluated with another method ?
  - Use mechanical position of the collimator ?

Average 256 pixels frame at the center of the FoV





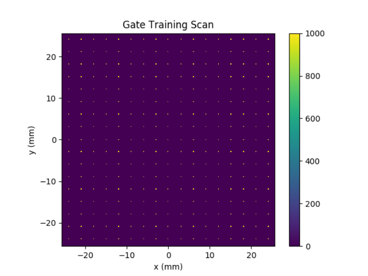
- Gate Optical Simulation
  - Light distribution not perfectly reproduced
  - Can strongly affect exp data reconstruction

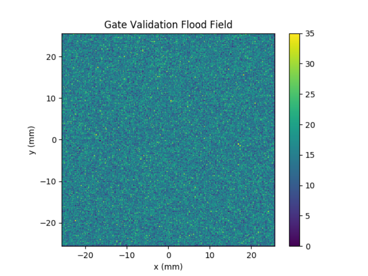
$\Rightarrow$ Gate optics simulation scan to optimize (find best parameters)
$\Rightarrow$ Experimental scan for training.

Monte Carlo Data

- Gate optical MC simulation for generating both training and validation data sets
  - 1 *Scans* of (17×17) positions with 1000 γ events each.
    $\Rightarrow$ Training
  - 1 *Flood field* of 1 million events. $\Rightarrow$ Validation

Simulated *Scan* and *Flood field*

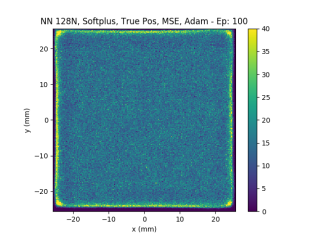


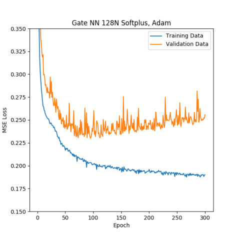


$\Rightarrow$ Network parameters optimization.

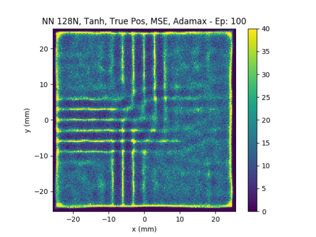
NN Parameter Optimization

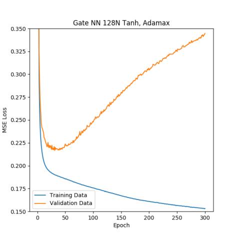
Good neural network parameters



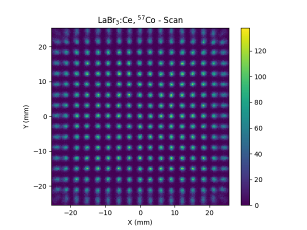


Bad network parameters

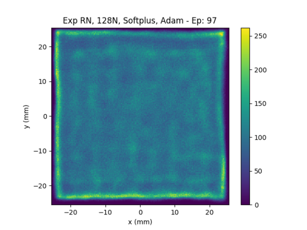




Exp. Scan Collimated ^{57}Co

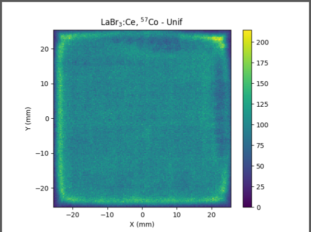


Fully Connected Network



⇒ Stronger distortions compared to fitting method but faster than at least one order of magnitude.
⇒ Still requires some parameters tuning.

terative fitting method



Conclusion

- NN Optimization based on Gate MC simulation

- Future
  - Better quantification of NN (based on the image)
  - Parameter fine tuning
  - Better training values (based on other methods)
  - Add Depth of interaction computation

Thanks for your attention !