Study and Optimization of Positioning Algorithms for Monolithic PET Detector Blocks

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Abstract

We are developing a PET insert for existing MRI equipment to be used in clinical PET/MR studies of the human brain. The proposed scanner is based on annihilation gamma detection with monolithic blocks of cerium-doped lutetium yttrium orthosilicate (LYSO:Ce) coupled to magnetically-compatible APD matrices. The light distribution generated on the LYSO:Ce block provides the impinging position of the 511 keV photons by means of a positioning algorithm. Several positioning methods can be implemented to extract the incidence position of gammas directly from the APD signals. Finally, an optimal method based on a two-step Feed Forward Neural Network has been selected. It allows us to reach a resolution at detector level of 2 mm, and acquire images of point sources with a first BrainPET prototype.

Neural networks provide a straightforward positioning of acquired data once they have been trained. Therefore the critical work was to find a time-efficient training method without degrading the good spatial resolution reached. An optimization process has been carried out showing that the amount of training data can be reduced to about 5% of the initial number with a degradation of spatial resolution of less than 10%.

The BrainPET Scanner

- Cylindrical insert for MRI equipment.
- 52 cassettes of 4 detector blocks each one, with inner diameter of 40 cm.
- A detector block = two LYSO:Ce trapezoidal monolithic crystals of 10 mm thickness and 18.5x 21.4/22.4 - 22.5/23.5 mm surfaces, radially stacked.
- Each block is white painted (BC-620) and optically coupled to two APDs matrices, Hamamatsu S8850-02 (8x8 pixels per block detector).
- Individual front-end electronic based on the ASIC VATA-241, which sums the APD charge along rows/columns and generates a trigger by means of a CFD.

Necessity of a Positioning Algorithm in PET Monolithic Blocks

- Gamma incidence point + Incidence angle → Line-of-Response.
  (e_Z, e_T) (α) (LoR)
  - **No need for deep-of-interaction (DOI) determination.**
- The identification numbers (IDs) of the detectors triggering in coincidence provide the angle α.
- Scintillator light distribution depends on α and (e_Z, e_T).
- APDs measurements, Incidence angle, α $\xrightarrow{\text{Positioning Algorithm}}$ (e_Z, e_T) → LoRs → Images.

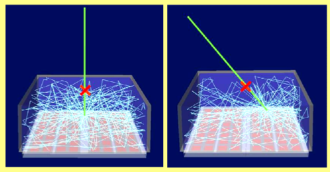

Fig. 1. Dependence of the scintillator light distribution on the incidence angle for the same incidence point on the detector's surface.

Positioning Algorithm Selection

- **Simulations of perpendicular and slanted incidence** of 511 keV gammas over a LYSO:Ce monolithic block have been developed with GAMOS, a CIEMAT Geant4-based Monte Carlo simulation software.
- Studied positioning methods: Anger Logic, Least Squares (LS, Chi^2, Generalized Chi^2), First and Five Nearest Neighbours (1NN, 5NN), one-step and two-steps Neural Networks (NN^G and NN^{G+L}).
- Optimal spatial resolution (FWHM) with a **two-steps Feed Forward Neural Network,** NN^{G+L}.
  - **Improvement above 40%** over the second-best algorithm.

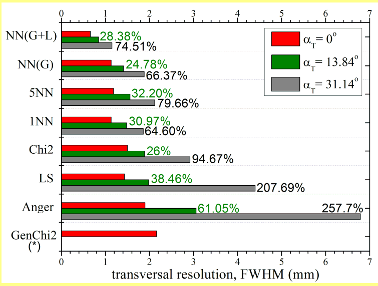

Fig. 2. Transversal spatial resolutions for three transversal incidence angles α_T for several positioning methods. Variations with respect to normal incidence are reported as percentage values.

(*) Very slow convergence, not repeated for slanted cases.

Neural Network Structure (NN^{G+L})

- One independent NN for each coordinate (e_Z, e_T).
- 8 inputs (APDs sums in rows or columns, x_i).
- 2 hidden layers of 4 sigmoidal neurons each.
- 1 linear output, $y = e_Z$ or e_T.

$$y = b + \sum_{k=1}^{4} \lambda_k \cdot \sigma\left(b_k + \sum_{j=1}^{4} \upsilon_{jk} \cdot \sigma(b_j + \sum_{i=1}^{8} \omega_{ij} \cdot x_i) \right)$$

- **Two-steps application** (Global + Local)
  - The first estimated coordinate (global) allows to select a restricted interval for a second (local) network.

First Brain PET Prototype

- Two detector blocks in coincidence and a rotating platform placed between them.
- **Each block was trained individually** working in coincidence with a PMT:
  - 300 events in known positions on a grid of 1 mm separated points over the entire block surface (525 points)
- Spatial **resolution at detector level** with NN^{G+L} ≈ **2 mm FWHM**.
- **Images of point ^{22}Na sources** reconstructed with SSRB + FBP.
  - Spatial **resolutions** with NN^{G+L} from **2.1 to 2.5 mm FWHM**.
  - Resolving power with NN^{G+L} ≈ 2 mm.

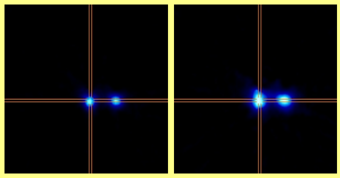

Fig. 3. Reconstructed images of two ϕ = 1mm ^{22}Na sources placed at 5 mm separation using as positioning algorithm NN^{G+L} (left) and 5NN (right).

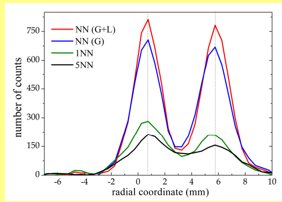

Fig. 4. Intensity profiles along the radial line that crosses the source centres for different positioning algorithms.

Optimization of the Training Procedure

Objective: To reduce the data acquisition and processing times without introducing a noticeable degradation of the detector performance.

Reduction of the Number of Events per Point

- Training can be done with **the sixth part of the initial data** with only a 3% of degradation on resolution.

Reduction of the Number of Training Points

- Based on the similitude of the light distributions of events with a common incident coordinate.
- Original training procedure: 23 points (e_Z, e_T') are associated to the coordinate e_T'.
- Proposed reduction: only a fraction of (e_Z, e_T') points are used for training.
  - Subsets of 4, 3 and 1 points per line e_T' have been tested.
  - By using a **32% subset of training points** degradation is only 3.6% FWHM.

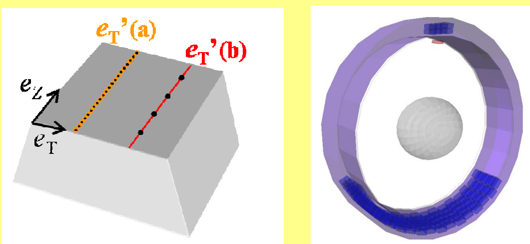

Fig. 5. Left: Reduction of the training points per line e_T' from 23 (a) to 4 (b).
Right: Sector of cassettes that generates valid coincidences with the block under training.

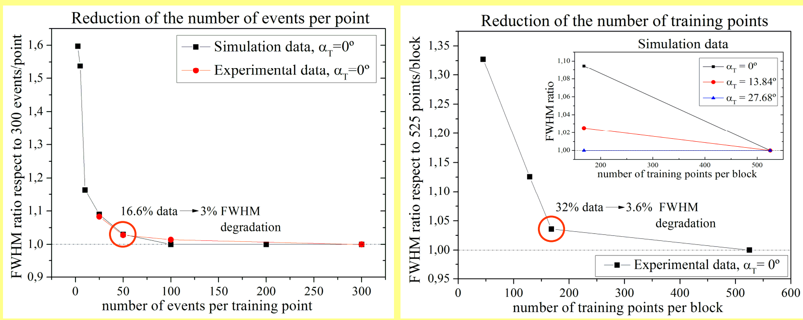

Fig. 6. Spatial resolution dependence on the number of training events per point (left) and on the number of training points (right).

Continuous Training Method

- Each block is trained in coincidence with the 17 cassettes placed in front of it (FoV ≈ 21 cm)
  - 17 transversal + 4 longitudinal NNs per block.
  - Displacing ^{22}Na point source placed on known positions close to the entrance block surface.
  - Coincident crystal IDs + source position → gamma incident point
- Estimated time for full ring acquisition approximately two weeks.

Result: A 5% of the original train data set leads to a resolution degradation lower than 10%.

Conclusions

- Several algorithms have been studied in order to deal with the positioning problem in a monolithic detector block.
- A two-steps Feed Forward Neural Network method was selected as the best choice for our BrainPET project since it provides spatial resolutions clearly better than the remaining algorithms.
- Spatial resolutions of 2 mm FWHM at detector level, and 2.5 mm in tomographic images of point sources were obtained with a first BrainPET prototype.
- An optimization for the full ring training procedure has been carried out, reaching a trade-off between temporal requirements and spatial resolution.
- The full scanner training acquisition time has been reduced to an estimated time of about 2 weeks.

[1] P. Rato Mendes et al., "Optimization of a monolithic detector block design for a prototype human brain PET scanner," 2008 IEEE Nuclear Science Symposium Conf. Rec., 2008, pp. 4927-4930.
[2] I. Sarasola, et al., "A novel front-end chip for a human PET scanner based on monolithic detector blocks," *12th International Workshop on Radiation Imaging Detectors IWORID2010*, Jan. 2011, JINST 6 C01034 2011.
[3] I. Sarasola, et al., "PET Demonstrator for a Human Brain Scanner Based on Monolithic Detector Blocks," *IEEE Trans. Nucl. Sci.*, [in press]