IMPET - Industrial Multiphoton PET Tomography

EVENT-LEVEL MACHINE LEARNING FOR COMPREHENSIVE PET COINCIDENCE CORRECTION

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IMPET

The IMPET project proposes innovative, AI-enhanced multiphoton imaging solutions for industrial applications:

- *Porous Materials*: novel 3D imaging – Quantum Decoherence modelling or Positronium Lifetime (PLI) for spatial analysis of pores and defects.
- *Opaque Fluids*: enhanced Positron Emission Particle Tracking for dynamic flow analysis in opaque fluids (e.g. liquid metals as nuclear reactor coolants).
- *The Goal*: industrial scanner design and software for scientific and commercial use capable of Positron Emission Particle Tracking (PEPT) and quantum decoherence imaging.

Problem

- PET image resolution is fundamentally limited by Compton Scattering and Accidental Coincidences, among other effects.
- Those two effects are amplified in LAFOV PET scanners with the increase of oblique LoRs.
- Classic and ML correction techniques do not account for other modalities:
  PLI, PEPT, $3\gamma/2\gamma$ and Quantum Decoherence.
- Existing ML models typically operate in the image domain, neglecting event-specific data.

Dataset

Training and validation datasets are generated using GATE 9.4 [2] Monte Carlo simulations of the Siemens Biograph Vision Quadra LAFOV scanner [1]. The XCAT anthropomorphic voxelised phantom [3] with 50 MBq activity is used to create list-mode data with complete "ground truth" event labels. An energy resolution of 9% FWHM at 511 keV is simulated at the digitiser level, while time resolution of 93 ps is applied in post-processing. An original algorithm is used to identify inter-detector scatter events. Events are classified into 4 classes: 49% true, 25% scatter, 10% detector scatter, 16% random.

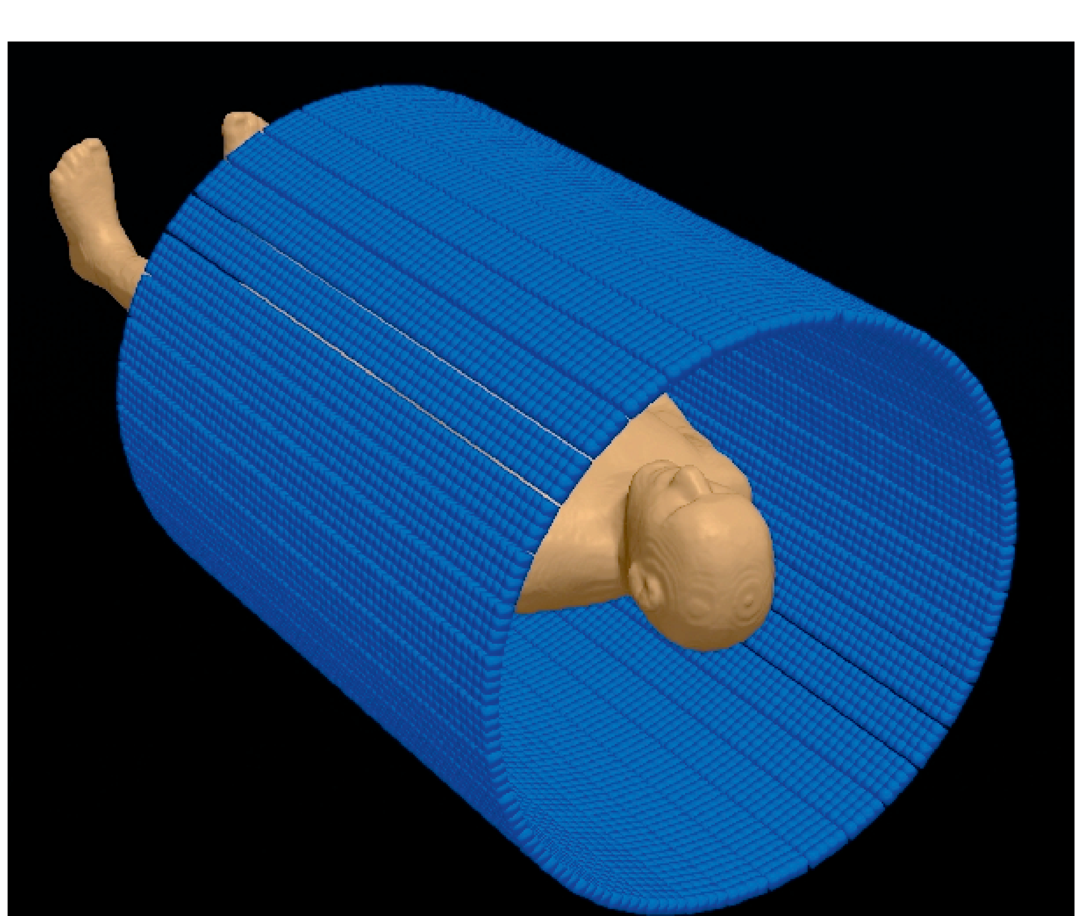

Figure: GATE model of Siemens Biograph Vision Quadra with XCAT phantom.

Encoding

Key innovation – 3D spatial encoding of coincidences for use with CNNs. For each ToF-estimated emission position, a 3D Gaussian ellipsoid is constructed, representing the spatial probability. The CNN receives a 3D volume defined as $\pm 3\sigma_{\perp}$ and $\pm 3\sigma_{\parallel}$ around the emission position. The input voxel image has two channels:

- positional ellipsoid, major axis along the LoR
- cutout of attenuation map

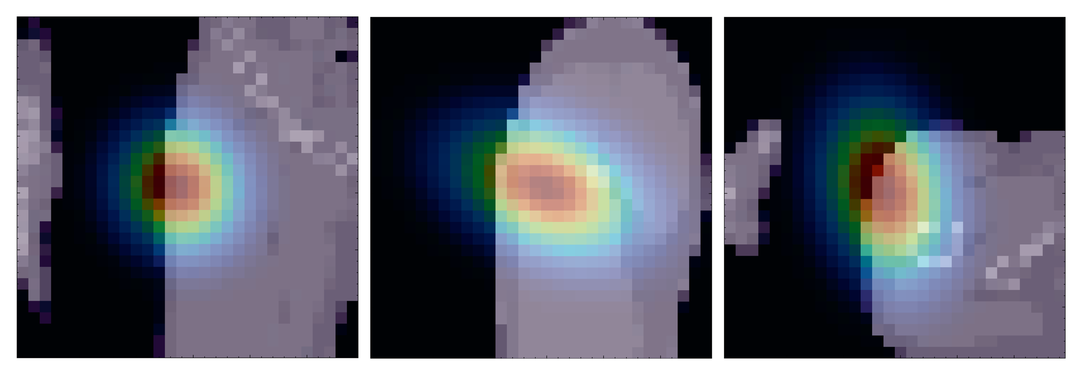

Figure: Slices of the 3D visual encoding of a coincidence: coronal, sagittal, transverse.

Model

A modified (full 3D) ResNet-18 serves as the CNN backbone, with physical event parameters – energy difference E_{diff}, energy sum E_{sum}, and time difference Δt – concatenated on top of the backbone. The network is trained in two modes:
Classifier (cross-entropy loss): 4 output logits, with two inference variants: (1) *argmax* – each event is assigned to the most probable class (one-hot), and (2) *softmax* – logits are passed through softmax to estimate per-event class probabilities.
Simplex regressor (tetrahedron MSE loss): output encodes 3D coordinates, vertices of a regular tetrahedron represent 4 classes; the proximity to each vertex encodes per-event class probabilities.

Results

A naïve, ToF-based reconstruction is performed by accumulating per-event weights in 3D voxels: binary weights for *argmax*, per-class probabilities for the *classifier* and the *simplex regressor*. Standard post-processing is applied: Gaussian and median smoothing, sensitivity and attenuation correction, SUV normalisation, and attenuation-derived body mask. To quantify the quality of the corrected images, two metrics are evaluated.

First, the ratio of corrected images to the true class (ground truth) image shows the best uniformity for the softmax classifier. Second, the MSE between the corrected and ground-truth 3D images is calculated for the body-masked region. The softmax classifier is the most accurate.

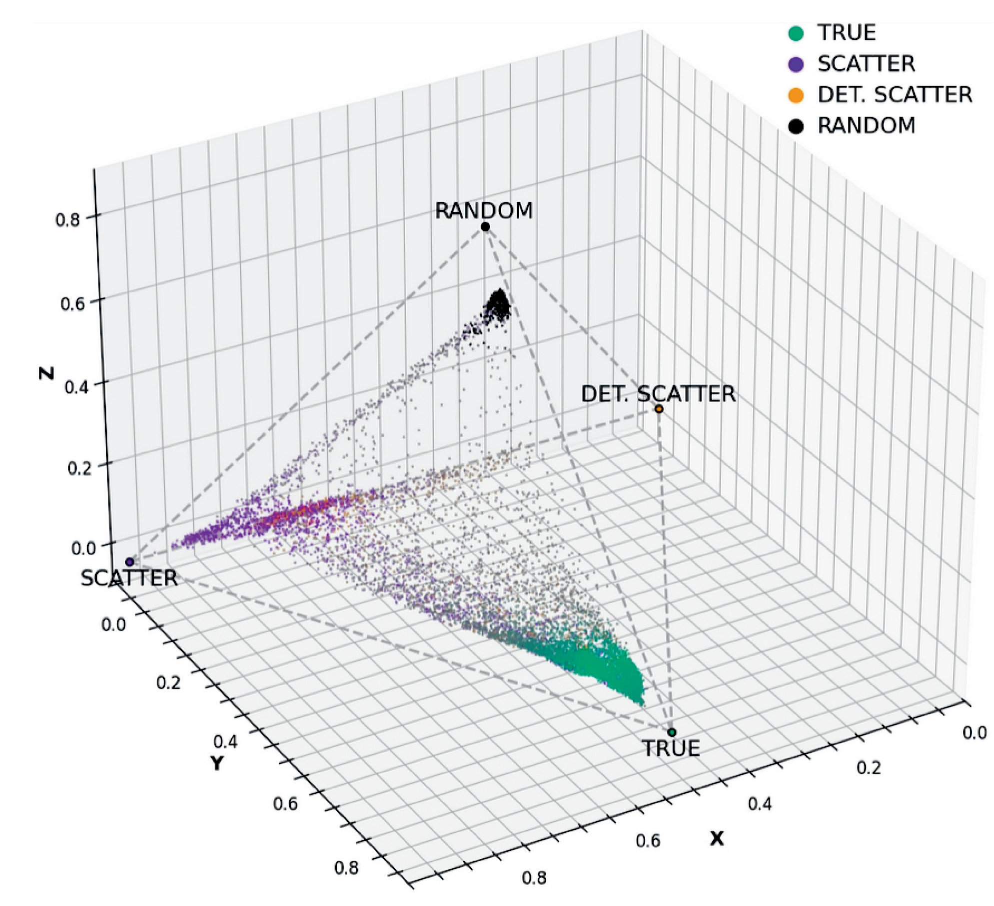

Figure: Visualisation of simplex regressor predictions: each point represents a predicted 3D coordinate, colour-coded by ground truth class.

Baseline	argmax	simplex	softmax
0.0189	0.0022	0.0021	**0.0012**

Table: MSE for the baseline and corrected images.

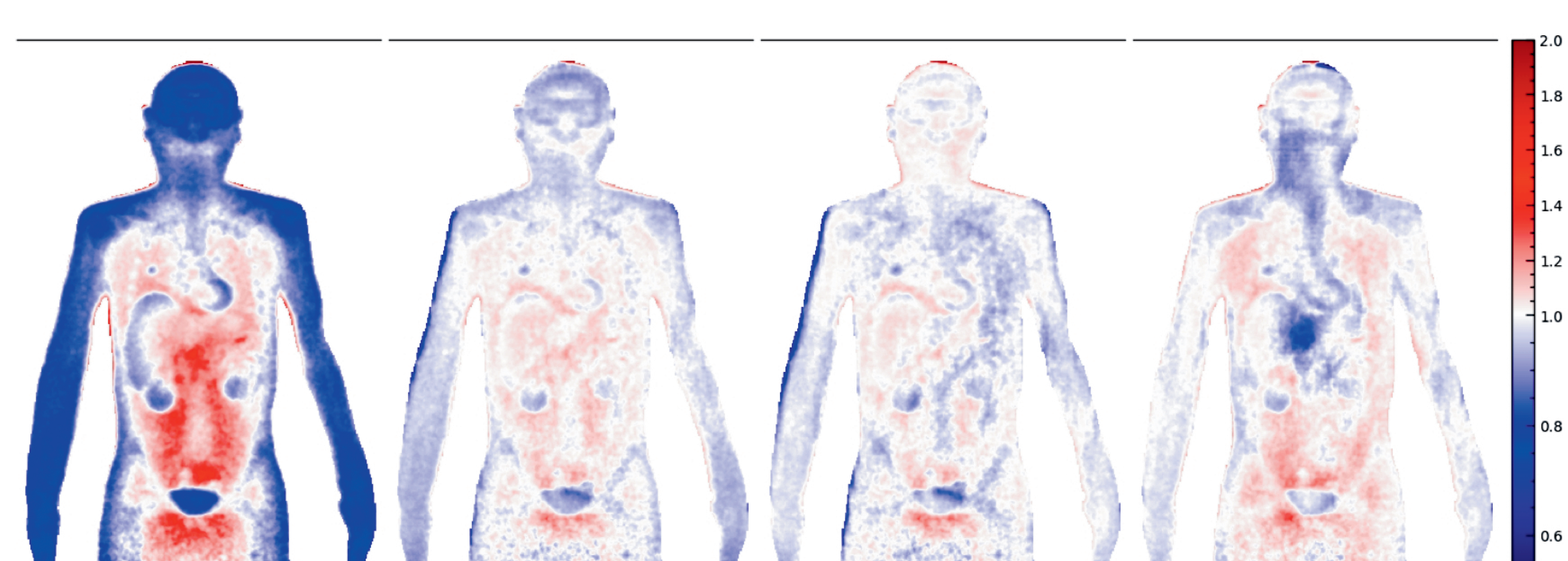

Figure: Central slices of ratio maps (predicted true / *ground truth* true) for: all events without correction (left), *argmax* classifier, *softmax* classifier (centre), and simplex regressor (right).

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References

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