Machine Learning-based Scatter Correction for a Dual-Panel Positron Emission Mammography Scanner

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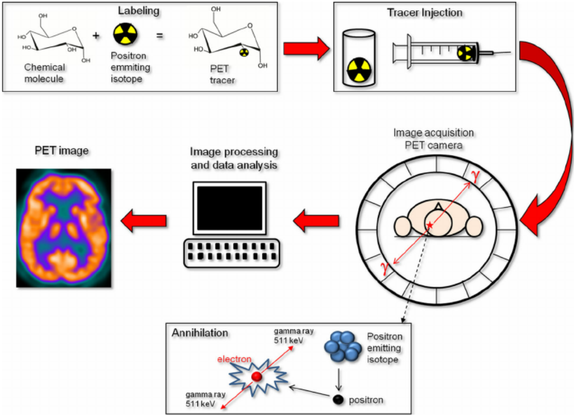
Nuclear Medicine



References

de Paula Faria, D., Copray, S., Buchpiguel, C., Dierckx, R., & de Vries, E. (2014). PET imaging in multiple sclerosis. Journal of neuroimmune pharmacology, 9, 468-482.

Corrections required in Positron Imaging

Main corrections

- Attenuation Correction
- **Scatter Correction**
- Random Correction
- Dead time Correction

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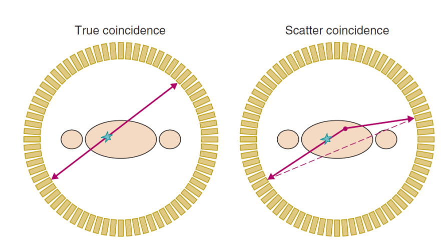
Types of coincidences



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Scattered Radiation

Scatter

- Interaction radiation with matter.
- Cross section for photons at $E_\gamma = 511$ keV.
- Compton Effect.
- $E_{\gamma'} = \dfrac{E_\gamma}{1 + \dfrac{E_{\gamma'}}{m_0 c^2}(1 - \cos\theta)}$

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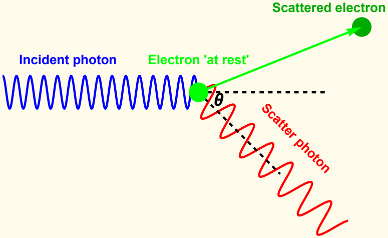
Compton Effect



Scatter Radiation Correction

Scatter Radiation Correction Methods

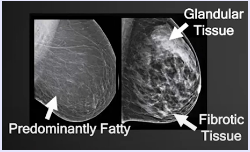
- Energy Window: From Dual Energy Window to Multiple Energy Windows: Applied on sinograms.
- Single Scatter Simulation: Computationally expensive and requires the μ-map of the patient.
- Extrapolation of scatter profiles outside of the object with smooth functions.
- Monte Carlo Simulations.
- Deep Learning based corrections.

References

- Zaidi, Habib, and Kenneth F. Koral. "Scatter modelling and compensation in emission tomography." European journal of nuclear medicine and molecular imaging 31 (2004): 761-782.
- Y. Berker, J. Maier and M. Kachelrieß, "Deep Scatter Estimation in PET: Fast Scatter Correction Using a Convolutional Neural Network," 2018 IEEE NSS/MIC, Sydney, NSW, Australia, 2018, pp. 1-5.
- C. C. Watson, "New, faster, image-based scatter correction for 3D PET," 1999 IEEE NSS/MIC. Seattle, WA, USA, 1999, pp. 1637-1641 vol.3

Breast imaging

Screening



Depends on the breast density ($\sim$ 9% of positive cases are not detected).

Breast imaging

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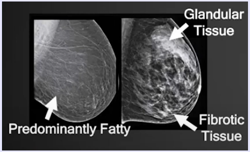
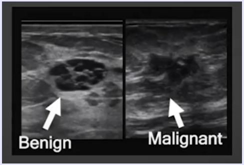
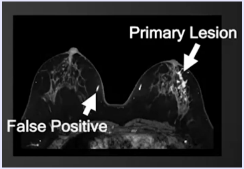


Depends on the breast density (∼ 9% of positive cases are not detected).

Complimentary tools: Ultrasound, MRI





Disadvantages: Dependency on the operator. The malignancy of the lesions are not distinguished (∼ 70 − 90% of the biopsies are unnecessary).

Breast imaging

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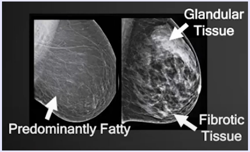

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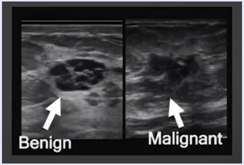

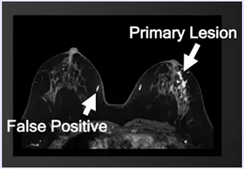

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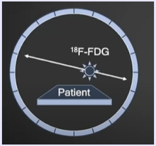
Nuclear medicine: WB-PET and PEM



PEM Advantages: Time for a study, Radiation Dose, Spatial resolution, Cost. Monitoring during treatment

References

- Claire Keun Sun Park (2021). Toward dedicated positron emission mammography and ultrasound-guided breast biopsy. OICR.
- Thompson, C. J., Murthy, K., Picard, Y., Weinberg, I. N., & Mako, R. (1995). Positron emission mammography (PEM): a promising technique for detecting breast cancer. IEEE transactions on nuclear science, 42(4), 1012-1017.

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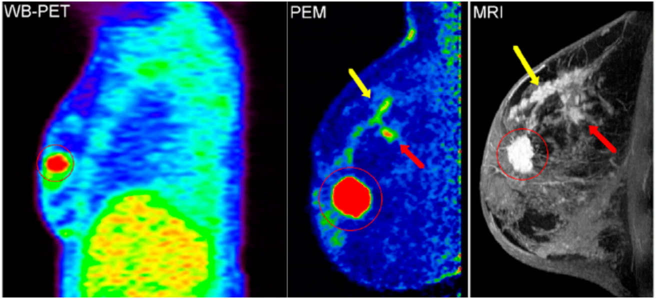

References

MacDonald, L., Edwards, J., Lewellen, T., Haseley, D., Rogers, J., Kinahan, P. (2009). Clinical imaging characteristics of the positron emission mammography camera: PEM Flex Solo II. Journal of Nuclear Medicine, 50(10), 1666-1675.

Positron Emission Mammography (PEM)

Advantages

- Better spatial resolution than WB-PET: Small and early stage tumor detection ($R_{esp} \approx 1 - 3mm$).
- Higher sensitivity than WB-PET: Smaller radiation dose to patients.
- Early detection of metabolic activity of cancer cells.
- Less amount of false positives: Reduction in the number of unnecessary biopsies.
- PEM scanner has lower costs than conventional PET.

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Challenges

- Dual Panel: Limited Angle Tomography.
- Commercial prototypes do not include attenuation and scatter correction.
- Quantification is not possible.

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- Glass, S. B., Shah, Z. A. (2013, July). Clinical utility of positron emission mammography. In Baylor University Medical Center Proceedings (Vol. 26, No. 3, pp. 314-319). Taylor Francis.
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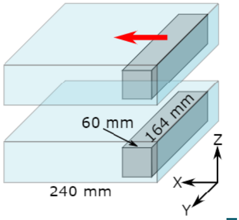

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Monte Carlo Simulation

Considerations

- Detailed simulation of the prototype of our lab.
- GATE.
- Positron source.
- Coincidence window: 6 ns.
- Energy window: $[350, 750]$ keV.
- Energy resolution: 13%.
- LYSO crystals.
- Simulation time: $60s$
- Concentration of Activity: 10 kBq/ml.
- Several phantoms.

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Output

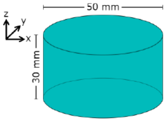
- Data: List Mode.
- Number of events: $\sim 10^6$ per study.
- File: *.root
- Information: $(X_1, Y_1, Z_1, X_2, Y_2, Z_2, E_1, E_2, S_1, S_2, \ldots)$.

Reference

Saaidi, Rahal, et al. "Crystal scatter effects in a large-area dual-panel Positron Emission Mammography system." Plos one 19.3 (2024): e0297829.

Phantoms

Uniformity (U)



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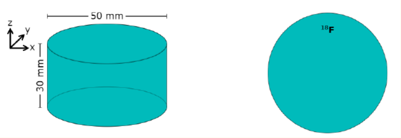
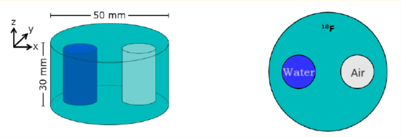


Spill Over Ratio (SOR)



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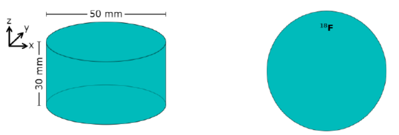

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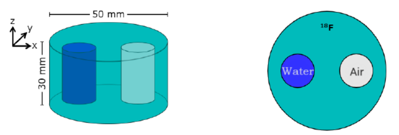
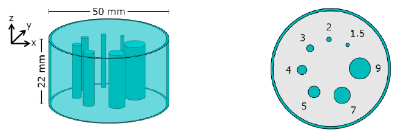


Recovery Coefficients (RC)



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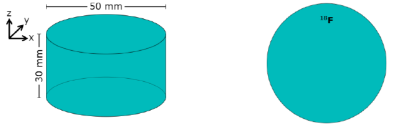

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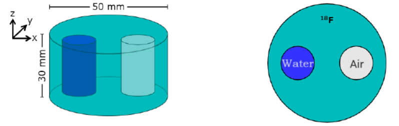

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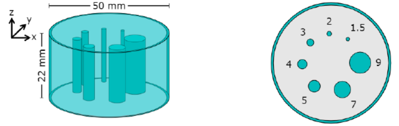
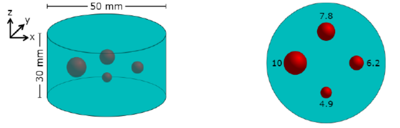


Contrast



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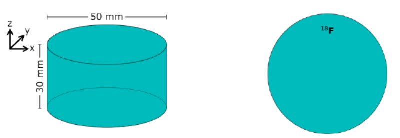

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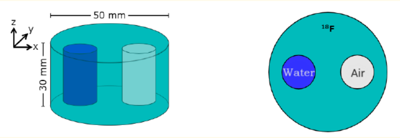

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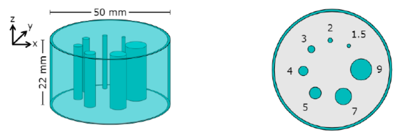

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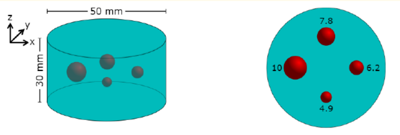
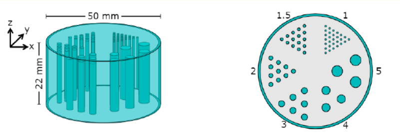
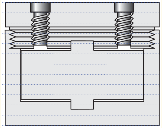


MiniDerenzo



Container



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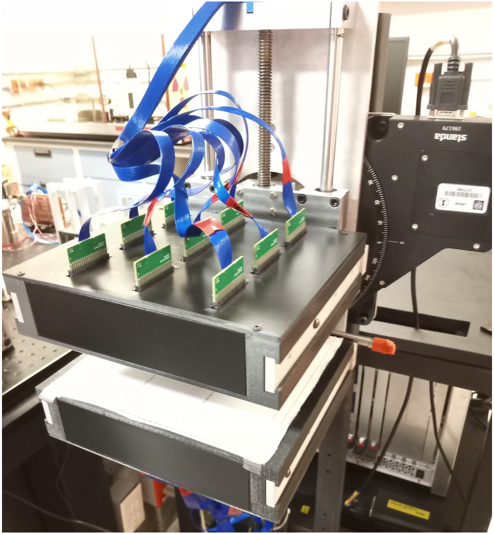
-Torres-Urzúa, Luis Fernando, et al. "A dedicated phantom design for positron emission mammography performance evaluation.” Physics in Medicine & Biology 65.24 (2020): 245003.

PEM Prototype



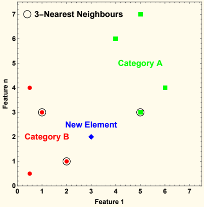
Machine Learning Models

Problem

- Binary Classification Problem.
- Question: Did any of the pair of detected photons undergo Compton Scatter in the phantom before being detected?
- Features: $X_1, Y_1, X_2, Y_2, E_1, E_2$.
- Label: **not** (S_1 **or** S_2)

Machine Learning Models

K-Nearest Neighbors



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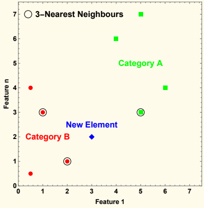
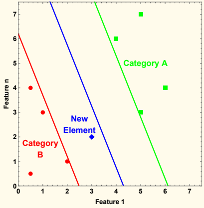


Support Vector Machines



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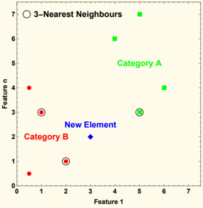
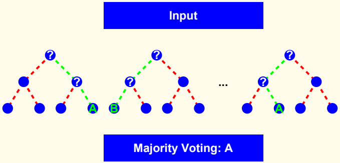


Random Forest



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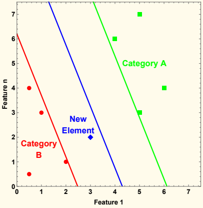

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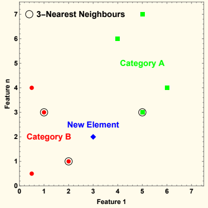

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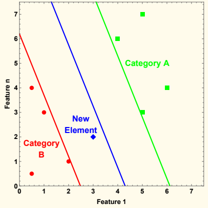

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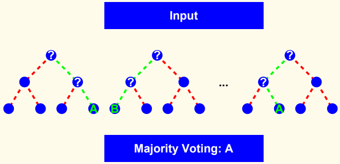
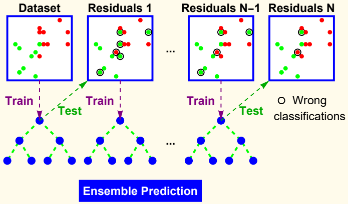


Gradient Boost



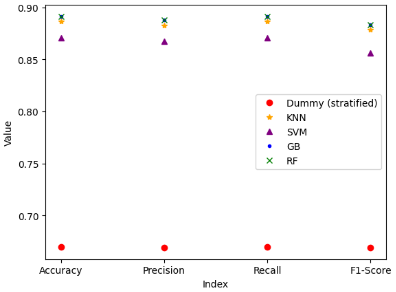
Machine Learning Models

Training

- Data pre-processing: StandardScaler()
- Hyperparameters: Grid Search
- Cross Validation: 5-fold.
- Score: F1-Score.
- Output: Scaler.bin, Model.joblib and ScatterFree.root

Machine Learning Models

Comparison of Models



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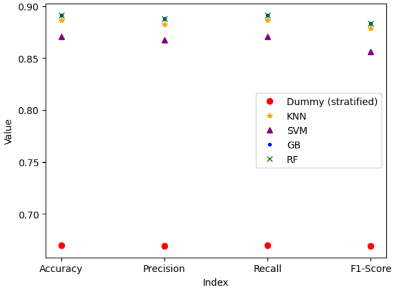

Equations

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

Machine Learning Models

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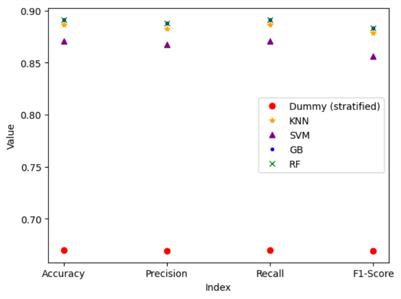

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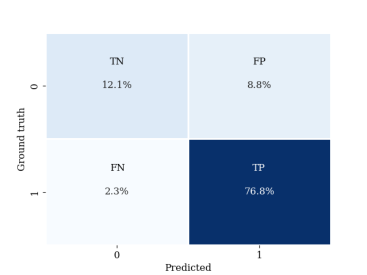
Set of best parameters: Random Forest

- Number of estimators: 34.
- Maximum depth: 12.

Machine Learning Models

Confusion Matrix



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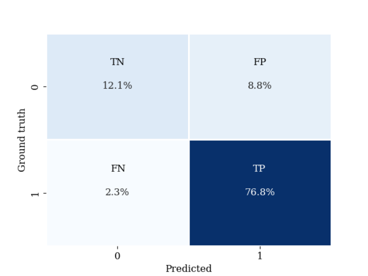
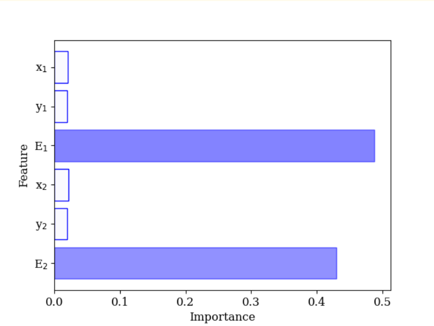
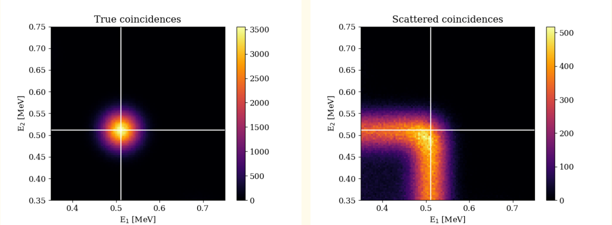


Feature Importance



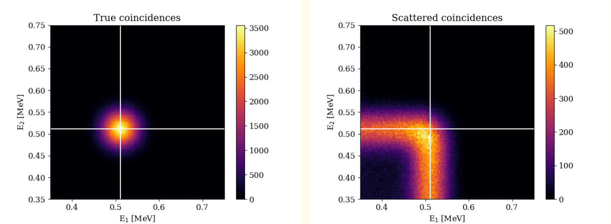
Energy distribution for true and scattered coincidences

Ground truth

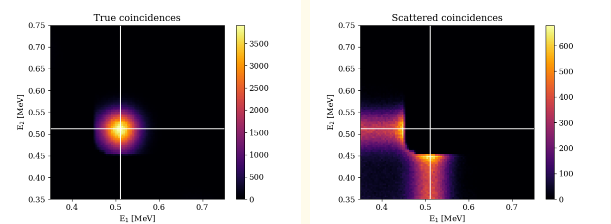


Energy distribution for true and scattered coincidences

Ground truth



Random Forest Predictions



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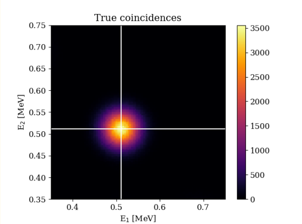
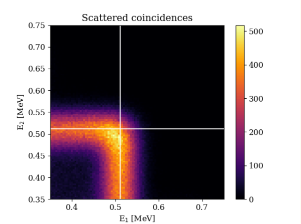
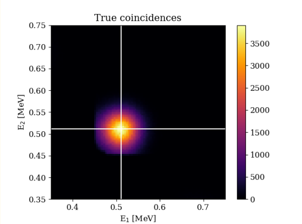
Energy distribution for true and scattered coincidences

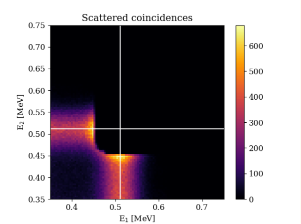
Ground truth





Random Forest Predictions



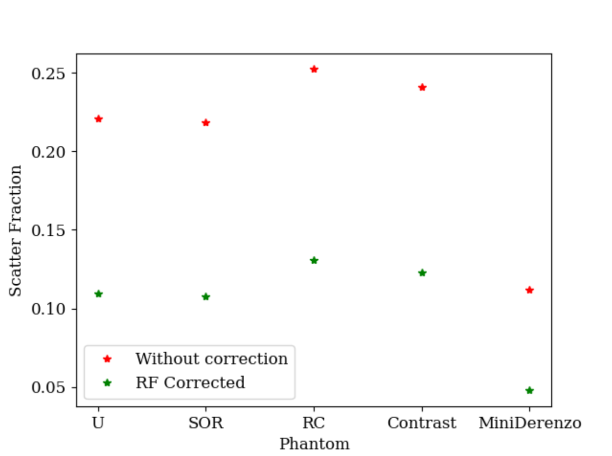


Note:

Energy resolution of the device is very important!

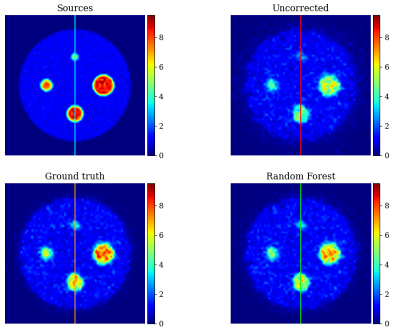
Machine Learning Models

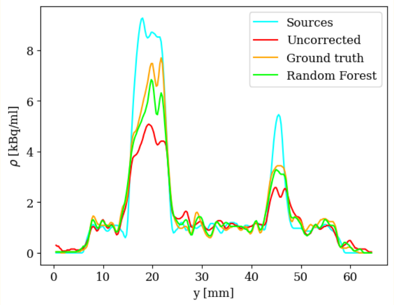
Scatter Fraction



Results

Reconstructed images: LM-OSEM (Castor)



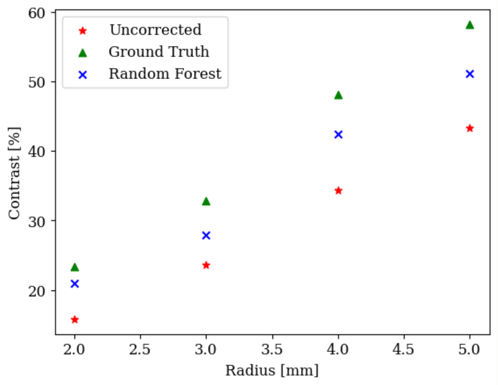


Lesions Phantom + Scattering shell (2 cm)

Results

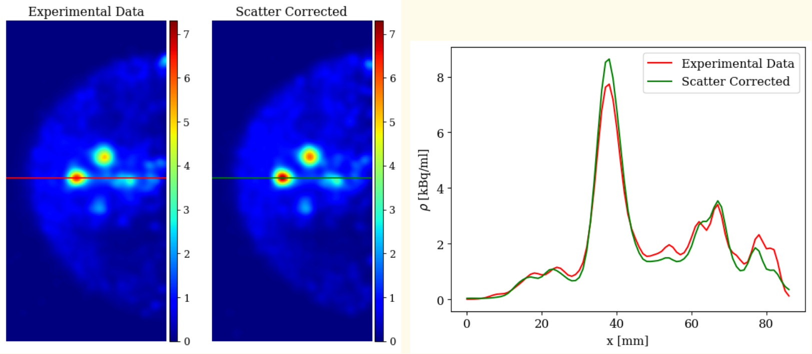
Contrast

$$C_j = \frac{\frac{I_j}{I_{bg}} - 1}{\frac{A_j}{A_{bg}} - 1} * 100\%$$



Preliminary Experimental Results

Experimental Reconstructed images: LM-OSEM (Castor)



Reference

Anayeli León, et. al. Quantification of tumour uptake in Positron Emission Mammography. Poster. XVIII MSMP.

Take home message

Concluding remarks

- Several Machine Learning models have been implemented for Scatter Correction in a Dual-Panel Positron Emission Mammography Scanner.
- The training data is acquired from Monte Carlo simulations
- Each pair of photons is analyzed individually by the Machine Learning Algorithm to see if it has undergo Compton Scattering or not (binary classification).
- The best results were found with a random forest:
  - Accuracy: 0.883
  - Reduction in Scatter fraction.
  - Better contrast.
- What's next?
  - To train the ML algorithms with voxelized phantoms.
  - More experimental data.
  - Towards quantitative PEM: To develop a framework for PEM scanner including scatter and attenuation corrections and mitigating the limited angle artifacts.

Dzięki!

Acknowledgment

We thank the support from PAPIIT grant IN108721, the Ph.D. scholarship of Fernando Moncada from CONAHCyT and the PAEP scholarship for the workshop.