

# **Positron-Range Correction for an On-Chip PET Scanner using Deep Learning**

C. Clement<sup>1</sup>, F. Pagano<sup>2,3</sup>, M. Pizzichemi<sup>2,3</sup>, G. Terragni<sup>2</sup>, M. Kruithof-de Julio<sup>1</sup>, A. Rominger<sup>1</sup>, S. Ziegler<sup>4</sup>, E. Auffray<sup>2</sup>, K. Shi<sup>1</sup> *1 Inselspital, Bern, Switzerland <sup>2</sup>CERN, Geneva, Switzerland <sup>3</sup>University of Milano-Bicocca, Milan, Italy <sup>4</sup>University Hospital, Munich, Germany* 

### **I. Background**

- Previously introduced On-Chip PET scanner designed for Organs-on-Chips OOCs) applications
- Three novelties in this work:
	- Developed realistic OOC phantom for Monte-Carlo **Simulations**
	- Adapted 3D MLEM iterative reconstruction algorithm to geometry of our scanner
	- o Trained Deep Learning model for image-to-image translation converting non-positron-range corrected images into positron-range corrected ones

- Create pairs of positron-range corrected (ground truth) and non-corrected images (input to the network)
- Randomly sample 400 placements for the hot point sources withing the compartments of the OOC phantom
- Conduct 800 simulations (400 each with F18-positron point sources and corresponding back-to-back gamma point sources)



## **II. Methods**

- Use list mode-based MLEM iterative reconstruction algorithm implemented with QETIR
- Parameters: image dimensions 800 x 400 x 200, voxel dimensions of 0.1 mm x 0.1 mm x 0.1 mm, five iterations, and four subsets.

#### **A. Monte-Carlo Simulation**

- Dataset generation to train positron-range correction algorithm using GATE
- Simulation models scanner's response to either back-to-back gamma or positron sources placed in the compartments of the OOC phantom



#### **B. Dataset Creation**

- Left column shows non-positron-range corrected reconstructed image from the test set using F18-positron point sources
- Middle column shows corresponding positron-range corrected reconstructed images using back-to-back gamma point sources
- Right column shows DL corrected images coming from the trained model
- Top and bottom row show different intensity percentiles ranges to scale the images
- Table below depicts mean FWHM values of the line profiles drawn through the point sources in each compartment

Study's findings confirm DL-based positron-range correction algorithm's capacity to significantly enhance the quality of reconstructed images

#### **C. Reconstruction**

#### **D. Deep Learning-based Positron Range Correction**

This work was supported by the Swiss National Science Foundation under grant SNFN 200021\_188914. Calculations were performed on UBELIX [\(www.id.unibe.ch/hpc\)](http://www.id.unibe.ch/hpc), the HPC cluster at the University of Bern. This project receives support by the CERN Budget for Knowledge Transfer to Medical Applications.

- U-Net image-to-image network trained to predict positronrange corrected images from non-corrected ones
- Determine spatial resolution based on FWHM values of the line profiles dranw through the point sources of the phantom in the three dimensions

## **IV. Discussion and Conclusion**



- Positron-range effect is clearly visible when comparing the images from the left and middle columns
- DL-based approach improved the spatial resolution of the reconstructed images in the test set from FWHM values of 0.260 mm in the non-corrected images to 0.177 mm in the corrected ones
- Our approach improves the spatial resolution by almost 32%, which is more than 91% of the maximal achievable improvement of a FWHM value

Approach has the potential to advance the study of 3D models in radiopharmaceutical research and provide a valuable tool for radio pharmacists in the development of radio theranostics.

